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Exploring engineering-economic decision support for a future North Sea offshore grid

Doctoral thesis

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Aristotle, *The whole is more than the sum of its parts.*

Preface

The research presented in this thesis is carried out in a paper-based approach at the Department of Electric Power Engineering in the Power Systems group at the Norwegian University of Science and Technology (NTNU). Official supervisors during this work were Professor Magnus Korpås (Electricity Markets and Energy Systems Planning, NTNU), Professor Stein-Erik Fleten (Industrial Economics, NTNU), and Dr. Harald G. Svendsen (SINTEF Energy).

Parts of the work presented in this thesis have been published during the timeline of the PhD project; from January 2015 to January 2018. Most of the work was carried out at NTNU in Norway, but also during a semester abroad (fall 2016) at the Industrial Engineering and Operations Research Department at the University of California at Berkeley, USA, under the supervision of Professor Shmuel Oren.

The PhD was fully financed by NTNU. Additional funding and awards are acknowledged from Norges Tekniske Høgskole Fond, Tandberg Radiofrabrikk's Fond, Solbergfondet, Bay-Opt UC Davis, MOSEK Scholarship, 5th IAEE European Conference Presentation Award, and the EEX Group Excellence Award 2018.

Content of this thesis is intended for broad readership including both academics and practitioners. Use of jargons from engineering and operations research has been limited to best extent, in such a way that it will be easier to read for people that are unfamiliar with those disciplines. The main goal is to communicate current- and future challenges related to long term expansion planning, or strategic investment planning, and encourage use of suitable decision support tools to cope with this.

Oslo, 2019

Martin Kristiansen

Martin Kristiansen

Acknowledgements

There are many people whom I am very grateful to have shared this journey with. During my three years I have been fortunate to meet people from different corners in the world. Both through NTNU and during a research stay at University of California Berkeley.

First, and foremost, I want to thank my supervisor Professor Magnus Korpås for making these three years a part of my life to begin with. And for his trust in letting me pursue research relatively independently. I also want to extend my gratitude to Associate Professor Francisco D. Muñoz at Universidad Adolf Ibanez who has been an exceptional (unofficial) supervisor, as well as outstanding collaborator. I really appreciate the opportunity to work with such an expert within the field and for his humble guidance. Moreover, I want to thank Professor Shmuel Oren for his hospitality and guidance during my time in the US. Also, Dr. Harald G. Svendsen at Sintef Energy has been an indispensable source in helping me with programming and modelling work, and Professor Stein-Erik Fleten with bridging the gap between electric power- and industrial engineering which is an important corner-stone for this thesis.

I also want to thank friends and colleagues for collaboration, fruitful discussions and moral support; Philipp Härtel, Martin Hjelmeland, Carl Fredrik Rehn, Christian Skar, Hossein Farahmand, Camilla Thorrud Larsen, Ingeborg Graabak, Espen Flo Bødal, Markus Löschenbrand, Paolo Piscella, and others. Moreover, I am grateful for have had the pleasure to work with talented master students; Simon Risanger, Vegard Skonseng Bjerketvedt, Lars Åmellem, Erik Solli, and others. For both groups, I hope it was of mutual benefit. On top of that, I would like to thank Professor David Woodruff (University of California Davis) and Dr. Jean-Paul Watson (Sandia National Labs) for co-organizing their excellent PyomoFest in Trondheim where we manged to bring together people from academia and industry to learn and talk about optimization problems in the Energy- and Power Sector.

Finally, I want to thank my family, friends and girlfriend for their continuous support and encouragement.

Summary

This thesis presents work on decision support for long-term transmission expansion planning (TEP), i.e. the problem of deciding whether, where, when, and what infrastructure facility to upgrade or build. An adequate infrastructure is (today) necessary for interlinking power supply and demand at all times. However, both sides of this power (and energy) balance has been changing rapidly the last decade and is expected to continue doing so going forward – challenging the traditional planning problem. To this end, the main objective with this thesis is to explore methods and present analyses that are relevant for the planning process. This process is broken into three central stages:

- **Pre analytics**: Relevant data sources and how these are used to replicate a multinational power system, including statistical methods to reduce dimensionality.
- **Model development**: Optimization models that could simulate the dynamics of an interlinked power system, including solution algorithms that make large models tractable.
- **Post analytics**: Presentation of alternatives, tradeoffs, and impact, including ways to design energy policies and/or incentives for optimal investments to materialize.

The expansion planning problem encompass capital intensive investments, long time horizons, and large, physical systems spanning multiple countries. This with various elements that are interlinked and need to work together in order to keep the machinery going. Thus, a highly complex system (of systems) facing short- and long-term uncertainties. On top of that, there are individuals, companies and societies with varying objectives and incentives for current and future needs. As a result, an interdisciplinary approach is called for in order to break down the planning problem to its core. The disciplines listed below has been visited in course of the PhD project:

- **Power systems engineering**: Understanding the basics of power conversion (generation), power electronics, stability, and Kirchhoff's circuit laws (power flow).
- **Energy economics**: Power markets and design of capacity-, financial-, day-ahead-, intraday- and balancing markets. Being able to model and/or interpret everything between a monopoly to perfect competition.
- **Operations research**: Deterministic and stochastic optimization models that simulates the physical behavior and quantifies the value of current- and new elements in a system (e.g. transmission lines, storage or generators).
- **Game theory**: Non-cooperative and cooperative N-player games. The former for analyzing decisions and the latter for outcomes.

A majority of the results and findings are presented using the North Sea Offshore Grid, with surrounding countries, as a case study. Main takeaways include; (i) a high level of granularity in data is necessary for capturing operational tradeoffs in a system, (ii), scenarios should be exploited in order to account for uncertainty and its information value in terms of hedging (robustness) and options (timing), and (iii), by utilizing methods from controversial disciplines such as cooperative game theory and systems engineering, important insights could be gained. The latter primarily for communication and bargaining purposes, which in many cases could prove quintessential for investment decisions and/or policy designs. To this end, one of the most important contributions is a framework for multinational cost-benefit allocation schemes incentivizing cooperation in light of projections on future market integration and a cost-efficient utilization of resources in larger regions such as Europe, and the North Sea in particular. Other contributions include:

C1 Customized models for multinational TEP in an open source environment, programmed with Python (and the optimization library; Pyomo (Hart, Laird, Watson, & Woodruff, 2012; Watson, Woodruff, & Hart, 2012)). Both a deterministic and a stochastic optimization model, generic for multi-stage investment decisions.

C2 Case studies of a future, potential North Sea offshore grid using transparent, open-source data for year 2030. Main topics include flexibility needs and the role of interconnectors in market environments with varying shares of renewables (e.g. offshore wind), other flexibility providers (e.g. hydro, storage, gas, demand), artificial offshore wind power hubs (Power Link Island), and uncertainty (e.g. generation mix).

C3 Demonstrated the added value of applying methods from statistics, game theory, and systems engineering. This to reduce model dimensionality, account for bargaining power and estimate the value of efficient/fair payoffs/incentives, and systematically untangle complexities related to alternative solutions and tradeoffs.

Detailed methodologies, results and references are provided in accompanying papers whereas this thesis provides a stream-lined introduction to the motivation behind these, including important aspects of the three-folded planning process mentioned above. The reader should therefore get an overview of (i) data sources and how these could be processed (sampling and clustering methods), (ii), important aspects to consider when developing an expansion planning model, including model types (deterministic, stochastic, strategic) and solution algorithms (decomposition of coupling variables or constraints), and (iii), relevant methods to use for exploring model results, tradeoffs (multi-objective), and fair allocation schemes (e.g. when stakeholders or countries cooperate for the greater good).

Nomenclature

ACER	Agency for the Cooperation of Energy Regulators
CAPEX	Captial expenditure
DSM	Demand Side Management
EC	European Commission
EEA	Epoch-Era Analysis
EEV	Expected value of Expected Value solution
ENTSO-E	European Network of Transmission System Operators for Electricity
EPEC	Equilibrium Problem with Equilibrium Constraints
ESP	Equal Share Principle
EVPI	Expected Value of Perfect Information
IEA	International Energy Agency
ISO	Independent System Operator
LCOE	Levelized Cost of Energy
LP	Linear Program
MATE	Multi Attribute Tradespace Exploration
MCP	Mixed Complementary Problem
MILP	Mixed Integer Linear Program
MPEC	Mathematical Programming with Equilibrium Constraints
MSIP	Multistage Stochastic Integer Program
OPEX	Operating expense
OWP	Offshore Wind Power
PHA	Progressive Hedging Algorithm
PNBD	Positive Net Benefit Differential

PowerGAMA	Power Grid and Market Analysis (market simulator)
PowerGIM	Power Grid Investment Model (expansion planning model)
PV	Photovoltaic
ROV	Real Option Value
RVMS	Relative Value of Multistage Stochastic Programming
SDDiP	Stochastic Dual Dynamic Integer Programming
SIP	Stochastic Inter Programming
SP	Stochastic Programming
SV	Shapley Value
TEP	Transmission Expansion Planning
TSO	Transmission System Operator
TYNDP	Ten-Year Network Development Plan
VRES	Variable Renewable Energy Source
VSS	Value of Stochastic Solution

Contents

Chapter 1

Introduction

“ ”

Poul Anderson, *I have yet to see any problem, however complicated, which, when looked at in the right way, did not become still more complicated.*

Power systems represents the world’s largest machinery. Supply and demand has to be in balance at all times, ensuring a secure and reliable energy supply in an increasingly complex system with rapid technological changes at both sides of the equation. As a central part of forthcoming discussions, this changing landscape translates into a need for more sophisticated decision support tools and consequently technical challenges in size and complexity of those tools. The aim for this thesis is to assess relevant aspects for long-term power system expansion planning from a practitioners view – policy makers, system operators, or other third party analysts or academics. To this end, a particular focus will be weighted towards a multinational context relevant for Europe in general, and the North Sea Offshore Grid in particular.

1.1 Renewable integration and flexibility needs

Flexibility is a matter of importance when several countries in the European Union plan to incorporate large shares of generation from renewable energy technologies—particularly solar and wind power—in the coming decades (European Commission, 2011). Unlike conventional generation technologies, the variability and uncertainty of renewable resources, such as wind, solar, and run-of-river hydropower, result in higher needs for flexibility in order to maintain the reliability of a power system (Denholm & Hand, 2011). One source of flexibility is the possibility of balancing distinct generation resources and demand across large geographical areas through high-voltage transmission lines (Munoz, Hobbs, & Kasina, 2012; Konstantelos & Strbac, 2015). Distant wind farms, for instance, can present synergistic effects by geographic diversification (Hasche, 2010), which can reduce the need for other sources of flexibility such as storage and fast-ramping generation units. As a consequence, the power grid can increase the availability of multiple flexibility sources.

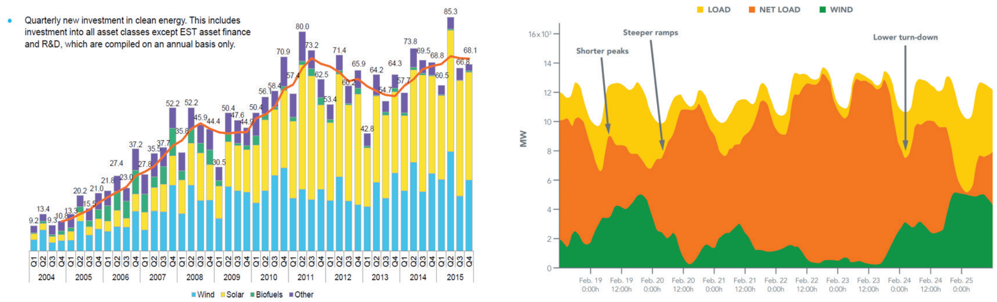


Figure 1.1: Increasing share of variable power generation capacity (left plot) causes more variations in net load (right plot). The net load (orange) has to be met with conventional supply or other flexibility options (e.g. demand, export, storage, fast-ramping supply). Left figure from Bloomberg New Energy Finance (Bloomberg New Energy Finance, 2016) and right figure from 21st Power Partnership (Cochran et al., 2014).

> Flexibility comes in two forms. The first, operational flexibility, refers to a systems' ability to cope with variability at short time scales (seconds to hours). An example of a flexible system composition could comprise wind and solar (variable), hydropower (fast-ramping and storage), and infrastructure (balance deviations in supply-demand). Recently, the demand side has also become an important contributor to flexibility (responding to price signals). The second, managerial flexibility, relates to long-term financial aspect of a system composition. For instance, in face of uncertainty, how flexible are investment decisions with respect to expanding or adapting to new trends?

Increasing share of renewables causes a variable net-load

The left part of Figure 1.1 depicts recent development in new generation capacity from solar (yellow bars) and wind (blue bars). These are not aggregated numbers, hence the accumulated development would have a much steeper growth – having its impact on supply-demand balance. The right part of Figure 1.1 illustrates the latter impact. Here, the net load (orange plot) represents the gross load (yellow plot) subtracted by variable generation capacity such as wind and solar (only wind is depicted with green plot). This means that the net load has to be covered by remaining sources or sinks in the system. Since the net-load varies significantly, and drop to zero at some times, it is crucial to have flexible supply or demand that can follow its steep changes – such as storage, hydropower and fast-ramping gas turbines, or maybe aggregate levels of flexible demand.

Renewable resources are often located far from load centers

The variability is one challenge. Another is that the most efficient renewable resources are often located far from load centers. Figure 1.2 demonstrates this with a geographical heat-map of wind speeds and solar irradiation throughout Europe. For instance, the highest wind speeds are not onshore, but at the coastline and preferably far offshore. The North Sea area is of particular interest as it is exposed to high wind speeds (Torbaghan, Muller, Gibescu, Van Der Meijden,

& Roggenkamp, 2014) (see Figure 1.2), surrounded by load centers and shallow areas like the Doggerbank (TenneT, 2017b).

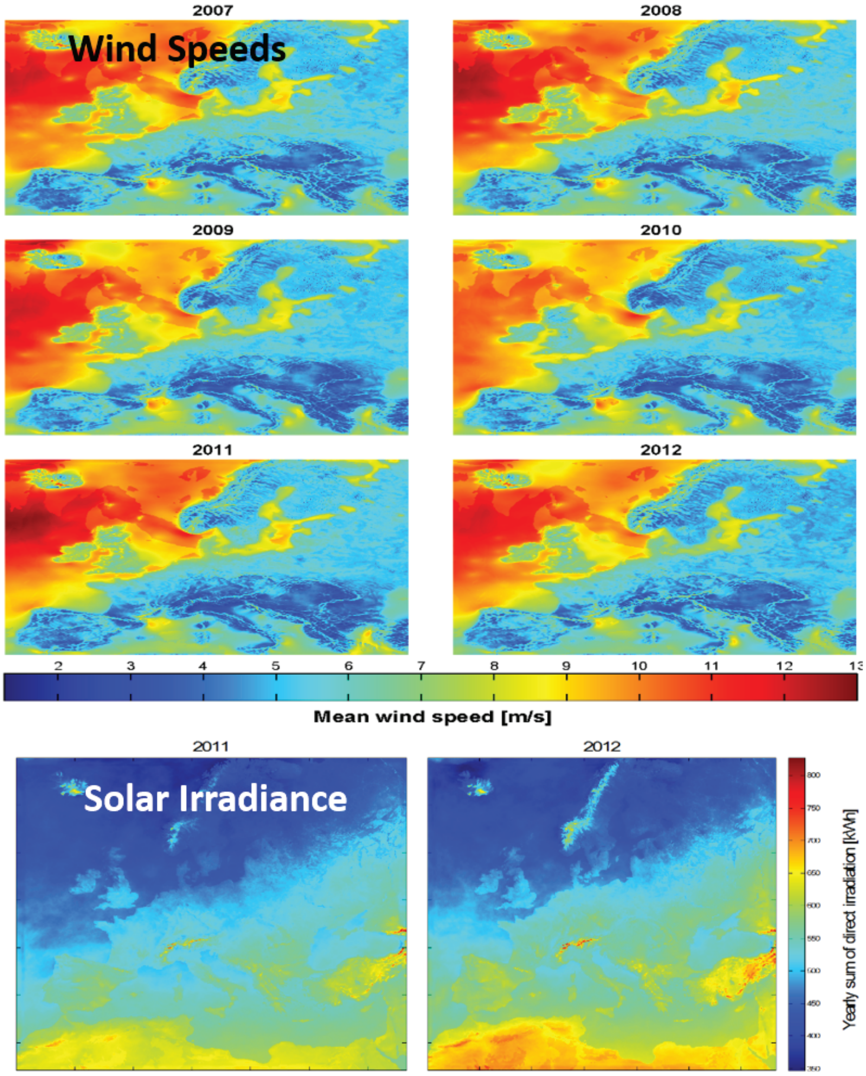


Figure 1.2: Yearly average wind speeds [m/s] and sum of direct irradiation [kWh] measured with numerical weather data in Europe. Strong wind resources in the North Sea are. Adopted figure with courtesy from Aigner (2013).

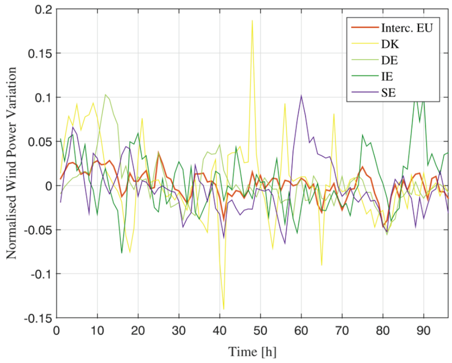


Figure 1.3: Wind power variation relative to installed wind capacity levels in different countries – Denmark (yellow), Germany (light green), Ireland (dark green), and Sweden (purple) – compared with the smoother, aggregate variations for an ideal interconnected system (red). Figure adopted from Malvaldi et al. (2017).

The smoothing effect of geographical diversification

Geographical diversification could help balancing out the rapid deviations in Figure 1.1. That is, from an European perspective, there is a small probability that the wind blows at the same wind speed in, e.g., Germany and Spain simultaneously. It is more likely that when wind speeds are high in one place, it could be lower at another place far away. This is known as smoothing effects (Hasche, 2010) with an example being the one depicted in Figure 1.3. The figure shows that the power feed-in to the power system is more volatile for a small portfolio of wind farms that are concentrated within a limited geographical (yellow, light green, dark green, and purple) area than a larger portfolio that is distributed across a larger, interconnected area (red line). Thus, for a strongly interlinked system one can utilize these smoothing effects which again could reduce the need for flexible response to this variability (as shown in Figure 1.1).

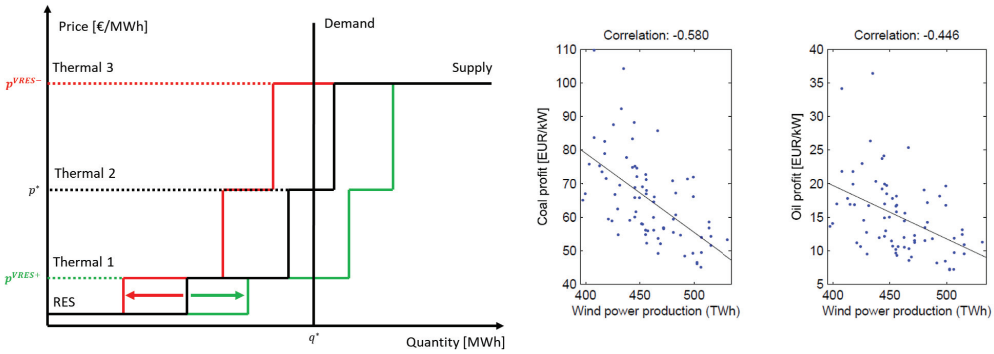


Figure 1.4: Left: Own illustration of the merit-order supply curves and the impact of increasing (green) or decreasing (red) supply of renewable resources (close to zero marginal costs). Right: Simulated impact on coal- and oil profits under an increasing share of wind power production (known as the merit-order effect) (Jaehnert, Korpås, Doorman, & Hyldbakk, 2015).

The merit-order effect of more renewables

It is expected that an increasing amount of renewable resources will shift the so-called merit-order supply curve as illustrated in Figure 1.4. Given the black colored supply curve as a base case, an increase of renewable supply capacity will shift the curve to the right (green), while a decrease will shift to the left (red). Given that everything else remains the same, an increase will result in that the market clearing goes from "Thermal 2" to "Thermal 1" as marginal producer, where the latter operates at a lower marginal cost. With perfect competition this means that the marginal cost will be reflected in the resulting price, p^{VRES+}.

The right part of Figure 1.4 shows a simulation of this effect on coal- and gas profits in the Northern European power system with 2030 data. It clearly demonstrates the decline in profits as more wind power penetrates the market clearing.

As of 2018, about 2% of all operational hours in Germany constitute negative prices due to the aforementioned merit order effect in combination with insufficient levels of flexibility (Bloomberg New Energy Finance, 2018). This is illustrated in Figure 1.5 where the supply is significantly lower than the demand during a weekend late October 2017 in Germany. Notice that dispatchable supply is still generating during negative prices, which is a sign of their inability to respond to rapid changes in the market. To this end, the figure clearly demonstrates the need for more flexibility. Flexibility could be provided in various forms, some of which includes:

- Flexible generation.
- Energy storage.
- Demand side management.
- Diversification/infrastructure.
- Market designs - capacity, day-ahead, and intraday.

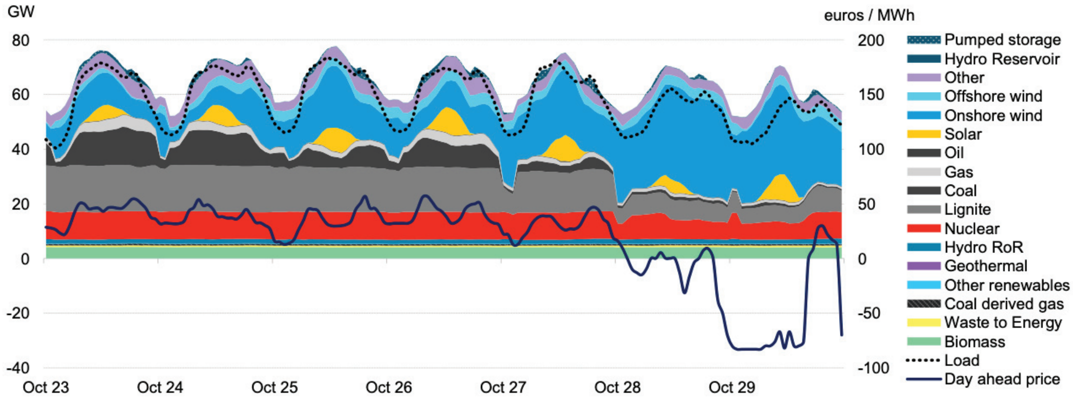


Figure 1.5: Negative prices in Germany during a weekend in October 2017. Due to lack of flexibility (flexible generators, storage, infrastructure, market design), about 2% of all hours during a year result in negative electricity prices in Germany. Source: Bloomberg New Energy Finance (Bloomberg New Energy Finance, 2018).

1.2 The role of an integrated grid infrastructure

With respect to the flexibility issues discussed in previous section, it stands to reason that grid can be a prominent contributor towards an efficient and sustainable development of the power system. This, for the following reasons:

1. Connect remotely located renewable sources.
2. Utilize geographical diversification of resources (smoothing effects (Hasche, 2010)).
3. Provide access to other flexibility sources (e.g. hydropower in Norway).
4. Enhance utilization of existing infrastructure.
5. Increase international trade of electricity and ancillary services.
6. Increased redundancy and security of supply.

The above assertions will potentially lead to other effects such as efficient utilization of resources and reduced GHG emissions (in spirit of the objectives outlined by the EU Commission (European Commission, 2011)). This is the reason why the North Sea Offshore Grid (NSOG) has been identified as one of the strategic infrastructure projects in EU Regulation No 347/2013. The regulation highlight the following qualifications for such projects; i) integrate renewable (offshore wind) resources, and ii), integrate markets for increased cross-border trade (European Commission, 2011, 2016). Hence, there is a top-down political force motivated by the aforementioned effects that potentially arise from a strong, integrated grid.

Long lifetime, uncertainty and (in)ability to adapt to changes

Due to the lumpy and irreversible nature of grid investments spanning 30-60 years lifetime, it is highly uncertain whether it will maintain a competitive edge in the future – where investment costs are recovered. For instance, distributed generation and batteries might lead to self-supplied load centers and, in extreme cases, become independent of grid connection as levelized cost of energy (LCOE) decline below the ones for conventional technologies (i.e. reach what is know as grid parity (Creyts & Guccione, 2014)). Moreover, other large-scale flexibility options might compete with grid and consequently drain some of its estimated value (Cochran et al., 2014; Kondziella & Bruckner, 2016; Kristiansen, Korpås, & Svendsen, 2018).

Large and non-divisible multinational grid projects can have a significant impact on future electricity prices, due to its lumpiness and episodic nature — contrary to less capital intensive investments that are continuous and marginal (Paul L. Joskow & Jean Tirole, 2003). This, in combination with strategic behavior, might result in inefficient investments seen from a free market, system perspective (W. W. Hogan, 2018). The latter has been a concern for adequate integration of renewables in Spain (Olmos, Rivier, & Prez-Arriaga, 2018) and similarly for the North-Western part in Europe (Grigoryeva, Hesamzadeh, & Tangers, 2018) where a centralized (multinational) approach is called for. Both cases conclude that a transparent and fair allocation of costs and benefits might be necessary to pave the way for efficient investments as a decentralized framework could fail in negotiating efficient outcomes (Narahari, 2014).

The importance of regional- and national cooperation

A majority of the projects planned in Europe, and particularly for the NSOG, are multinational as they span country borders. This is a challenge since these will only be realized if all the countries involved in their development reach an agreement on how to split benefits and costs (Gorenstein Dedecca & Hakvoort, 2016; Shariat Torbaghan, Müller, Gibescu, van der Meijden, & Roggenkamp, 2015). Alternatively, these transmission projects could be developed by merchant investors, but only if congestion rents from the arbitrage of power between countries provide sufficient revenues to cover their capital costs (Paul L. Joskow & Jean Tirole, 2003). This is in contrast to the challenge of developing inter-ISO[1] or interstate transmission projects in the US, where there exist rules that require regional planners to coordinate inter-regional projects if they could lead to cost-effective solutions for mutual transmission needs (e.g. , FERC order 1000 (FERC, 2012)).

> The inter-TSO compensation mechanism is designed to compensate for hosting cross-border flows, i.e. additional costs that occur in national transmission systems due to losses and facilitation of infrastructure.

ENTSO-E estimates €140bn worth of necessary electricity infrastructure upgrades the coming decade (ENTSO-E, 2016) in order to meet projections of demand and environmental targets. In light of these needs, and in order to speed up investments, Connecting Europe Facility (CEF) has decided to provide financial support netting €5.35bn. The inter-TSO compensation scheme is also set up in order to incentivize multinational collaboration by compensating countries for hosting cross-border power exchange, and for the domestic losses it might accrue. However, the budgeted ITC fund is currently not larger than €258m (Hirschhausen, Ruester, Marcantonini, & Seventh Framework Programme (European Commission), 2012). Several studies have addressed different grid designs and the added value of a North Sea Offshore Grid (NSOG) as a result of cost-efficient utilization of variables renewable energy sources (VRES), reduced greenhouse gas

1. Independent System Operators (ISOs) monitor and control the grid infrastructure by balancing demand and supply at all times. The same is the case for a Transmission System Operator (TSO), which is a term that is more common in Europe.

(GHG) emissions, and increased security of supply (Van Hulle et al., 2009; Egerer, Kunz, & Hirschhausen, 2013; Gorenstein Dedecca & Hakvoort, 2016). In (Strbac, Moreno, Konstantelos, Pudjianto, & Aunedi, 2014), the estimated benefits of an integrated NSOG range from €8bn and €40bn depending on the level of cooperation.

1.3 Planning for future grid investments

Transmission expansion planning (TEP) serves the purpose of determining an optimal plan for construction of new transmission lines in order to balance projections of the future supply- and demand mix. In that respect, it has to account for existing and planned developments in the power system, subject to operational-, economic- and regulatory constraints over a very long planning horizon (Munoz, Hobbs, Ho, & Kasina, 2014; Ciupuliga, 2013; Shariat Torbaghan, 2016). This, itself, represents a high degree of uncertainty. Hence, the nature of the TEP problem spans over multiple disciplines in order to understand to underlying drivers and value tradeoffs.

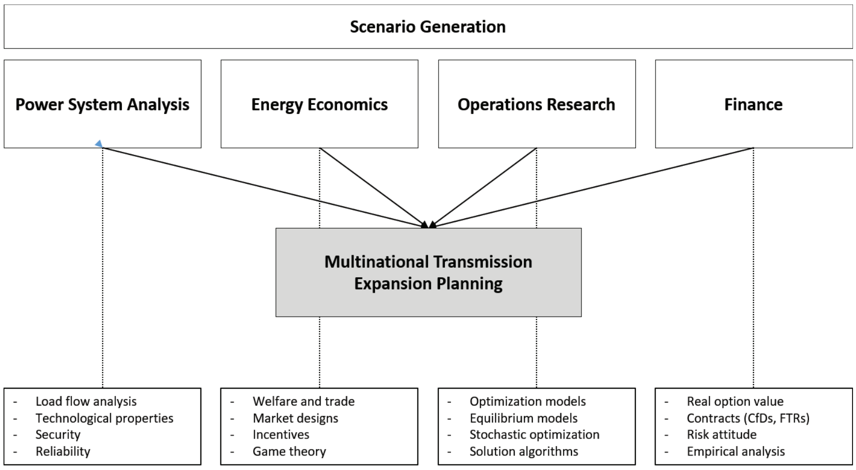


Figure 1.6: Various disciplines that could be present in the transmission expansion planning problem. Everything from Kirchhoff's laws to policy designs.

The main objectives are to decide whether, where, when, and what transmission technology to build while maximizing net economic benefits or minimizing system costs (Hobbs, Xu, et al., 2016) – hence a welfare-anchored problem due to its natural monopoly. However, due to the system complexities elaborated in the previous sections, this is not an easy task. Adding recent- and forthcoming trends on top of that, the planning problem becomes far more complex going forward – i.e. covering large geographical areas; anticipating what others do (transmission and generation); preparing for potential "flexibility competitors"; evaluating the right incentives for cooperation; and calculating cost recovery over a long lifetime under high uncertainty. To this end, there is a fair chance for inefficient and stranded assets without proper tools and analyses for decision support.

Transmission planning is an active area of study, particularly in the field of operations research. This is because finding a socially-optimal plan (e.g., the one that minimizes total system costs) from a set of candidate portfolios can be computationally challenging, even if all transmission investment decisions are made by a central authority (e.g., a national energy commission or a regulated transmission organization) (Latorre, Cruz, Areiza, & Villegas, 2003; Hemmati, Hooshmand, & Khodabakhshian, 2013). Large transmission networks can have millions of possible investment combinations and finding the optimal one might sometimes require the use of sophisticated optimization algorithms in combination with high-performance computers (Munoz & Watson, 2015). Also, in deregulated markets transmission investments can alter electricity prices and, consequently, incentives for investments in new generating capacity (Spyrou, Ho, Hobbs, Johnson, & McCalley, 2017b). Depending on the market structure, consideration of generator's response to transmission investments might require the use of equilibrium models that involve the implementation of non-trivial algorithms to find an optimal solution (Sauma & Oren, 2006; Pozo, Sauma, & Contreras, 2013). Uncertainty of input parameters such as demand, fuel costs, and carbon prices can also complicate decision making (Munoz et al., 2014; Munoz, Watson, & Hobbs, 2015), particularly if planners are risk averse (Munoz, van der Weijde, Hobbs, & Watson, 2017).

Additionally, the siting process of new transmission lines can be difficult if voluntary negotiations with landowners to obtain easements on private property fail, or if local communities or interest groups do not approve the development of new infrastructure in a determined area (Ciupuliga & Cuppen, 2013; Bertsch, Hall, Weinhardt, & Fichtner, 2016). However, these conflicts do not always result in cancellation of transmission projects. In many jurisdictions, regional transmission organizations are granted the power of eminent domain to develop infrastructure that is deemed necessary when voluntary negotiations fail (Meidinger, 1980; Rossi, 2009). Consequently, broad approval of transmission projects is desired but not strictly necessary in centralized planning settings.

Planning international transmission interconnections involves dealing with many of the difficulties mentioned above, but also requires consideration of additional features. Scale, for instance, is important because assessing the economic benefits of a proposed project between two countries requires concurrent simulation of operations in both systems in order to capture correlations of demand, wind, hydro, and solar profiles (if available). Scale becomes more relevant when evaluating the economic benefits that result from a set of multinational projects in an interconnected system with many independent countries or regions (Perez, Sauma, Munoz, & Hobbs, 2016, 4). However, the computational complexity that involves finding the so-called optimal plan in a large interconnected system (e.g., the one that minimizes expected system costs for the entire region, assuming full coordination among countries) is only a first step in a study of transmission interconnections. The next step involves finding a mechanism for allocating the economic benefits and costs that result from the proposed projects in a fair and efficient manner, such that all hosting countries support their development (see Paper H). Moreover, under certain circumstances, host countries might prefer to build a broader consensus and even consider the effects of new projects on third-party countries. As mentioned, those can experience positive or negative economic effects as a result of new grid investments elsewhere in the system (Bushnell & Stoft, 1996, 1997).

Key considerations

For the reasons mentioned above, providing adequate decision support is becoming more important than ever before. That is, everything from thinking hard about what one would like to achieve; creating tools to help capture the underlying value drivers; exploring options to exercise or postpone decisions; and doing ad-hoc analyses to communicate insights and providing the right incentives (energy policy). Incentives are important in context of this thesis, since the main case studies comprise multinational planning – which adds another dimension to the traditional planning problem (i.e. cost-benefit allocation). Hence, important considerations for TEP and the work presented in this thesis can be broken down to the following assertions (adopted from (Hobbs, Xu, et al., 2016)):

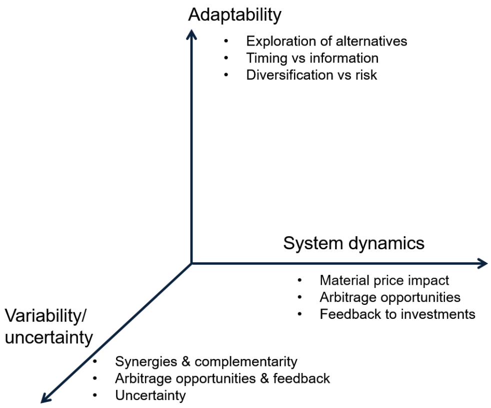


Figure 1.7: Key dimensions to consider in transmission expansion planning (Hobbs, Xu, et al., 2016). A fourth dimension would be the cost-benefit allocation problem (see Paper H).

1. *System dynamics* – how different technologies interplay and complement, or substitute, each other.
2. *Variability and uncertainty* – how system components respond to short- and long term changes.
3. *Adaptability* – system components and stakeholders ability to time responses and decisions in an efficient manner.
4. *Cost-benefit allocation* – understanding the incentives for cooperation and socially-optimal development plans.

First, 1), is primarily targeted for what is known as ”proactive planning”. That is, being able to anticipate how others, and particularly generators, react to transmission investments. Without further elaboration, the literature solves this by performing a co-optimization of both transmission- and generation assets (Sauma & Oren, 2006; Munoz et al., 2014; Alayo, Rider, & Contreras, 2017) exploiting the fact that a bi-level program can be recast as an optimization program under certain properties (Samuelson, 1952). This will account for arbitrage opportunities that arise as a result of the material electricity price impact of grid investments (W. W. Hogan, 1999a). Moreover, it is also related to being able to account for the effect of single versus multiple investments at the same time, or in different sequences. For instance, building transmission line A might have an impact on the profitability of the already existing transmission line B.

Short term variations, in 2), is about capturing interdependencies and synergistic effects at high temporal granularity (e.g. hourly variations) (Staffell & Pfenninger, 2018). It could be between technologies, geographical coordinates, and/or hours of the day, week, and year. For instance, solar PV and wind might complement each other on a seasonal basis as the wind blows the most during winter and the sun shines in summer time. Moreover, hydropower might provide flexibility in terms of fast ramping at hourly scale when the latter two variable sources rapidly changes its feed-in to the system. In the longer run, decision makers will face uncertainty like policy design, fuel prices, or innovation and capital costs for investments (and possibly new technologies) (Velasquez, Watts, Rudnick, & Bustos, 2016). Being able to hedge against risk/consequences of these uncertainties can add significant (expected) value – hereby referred to as ”robust decisions”.

Adaptability, in 3), is closely related to long term uncertainty in terms of making robust decisions that are well suited for a number of future scenarios. This could in some cases result in more diversified investments that function as an ”insurance”. Hence, one could be willing to pay a premium in order to have this insurance (Hobbs, Xu, et al., 2016). Additionally, timing decisions in face of uncertainty could also add what is known as ”real option value” (van der Weijde & Hobbs, 2012). For instance, by postponing decisions one could learn more about the future as uncertainty evolves into firm knowledge – thus the expected value of waiting.

As an additional point to the ones suggested by (Hobbs, Xu, et al., 2016), the allocation problem is also something that should be analyzed carefully – particularly for projects among multiple regions or countries. Recently, this has been identified as equally, if not more, important than building proper decision support tools (Lumbreras & Ramos, 2016; Gorenstein Dedecca & Hakvoort, 2016). No matter how good the model is, projects will not materialize if incentives are absent. Hence, although its more of an ad-hoc part of TEP, it is important to asses cost-benefit allocation schemes that outlines the proper incentives for projects to be developed. The biggest challenge might not be the cost allocation alone, but also a redistribution of expected benefits that usually exceeds costs by far in addition to being unevenly distributed (Paul L. Joskow & Jean Tirole, 2003; W. Hogan, 2011).

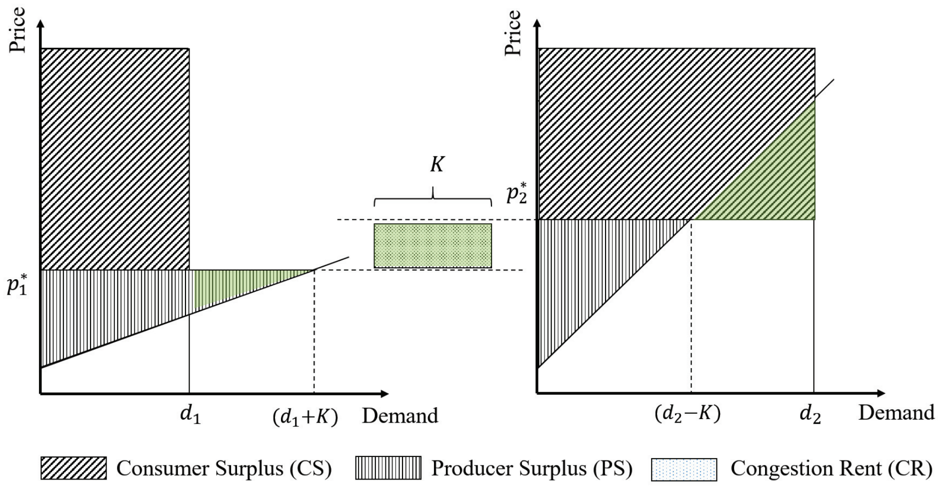


Figure 1.8: A simple example that illustrates the economic impact of expanding the capacity of a congested transmission corridor between two areas, 1 and 2. The resulting price difference determines the potential income for the expanded corridor, known as congestion rents (CRs).

Basic economics behind expansion planning

Efficient grid investments could emerge when a transmission corridor is congested, meaning that there could be price differences between each end of the corridor large enough to justify capital costs. The economics behind transmission expansion goes way beyond this simple example, but it might be beneficial for the reader to be aware of the basics.

Figure 1.8 demonstrates the basic economics behind an expansion of a congested transmission corridor between two areas, 1 and 2, that are considered as low- and high price areas, respectively. Area 1 will become an exporter at the new transmission line, leaving a surplus to the producers. From economics, we know that more goods and services leads increased welfare with a net impact being the green shaded area. Contrary, consumers will benefit in Area 2 due to lower prices through imports from the new line. The price difference at each end of the new line will determine the potential income from operating that transmission line, depending on i) the capacity, and ii) the price difference. Hence, the optimal transmission capacity will again depend on the objective of the investor; whether it is to maximize profits (merchant) or minimize costs for the system (welfare).

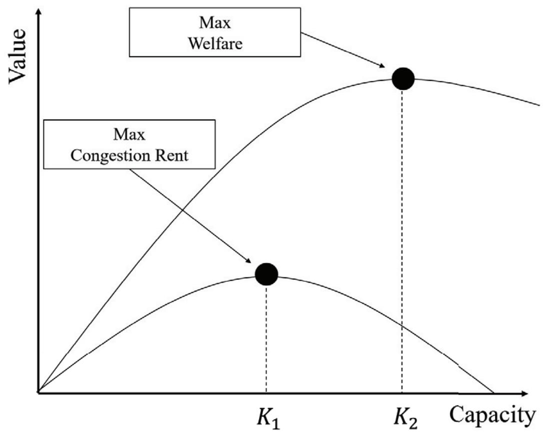


Figure 1.9: The optimal capacity of a new transmission corridor depends on the investor's objective; with two examples being i) maximize net congestion rents (merchant) or ii) maximize system welfare (cooperative).

The value functions for the two different types of investors are illustrated in Figure 1.9. Maximizing welfare, or minimizing costs, means that the investor's objective is to expand all congested lines till total costs are minimized. That is, when the marginal benefit of adding an incremental unit of transmission capacity is equal to its marginal investment costs. A welfare oriented investor will therefore add as much capacity as possible in order to avoid large price differences (higher operational costs for the system), which is denoted with optimal capacity K_2 in Figure 1.9. On the other hand, a merchant investor will seek to maximize the net estimated income for a transmission line, i.e. net congestion rents (CRs). The latter will result in lower optimal capacity levels than the welfare solution, $K_1 < K_2$, due to the quadratic product of capacity times price difference.

Figure 1.10 shows how costs and benefits are divided for the two different types of owners. A welfare investor will capture all costs and benefits, which consequently ends up benefiting both producers and consumers in a society. On the other hand, a merchant investor will isolate some of these costs and benefits, such as CRs.

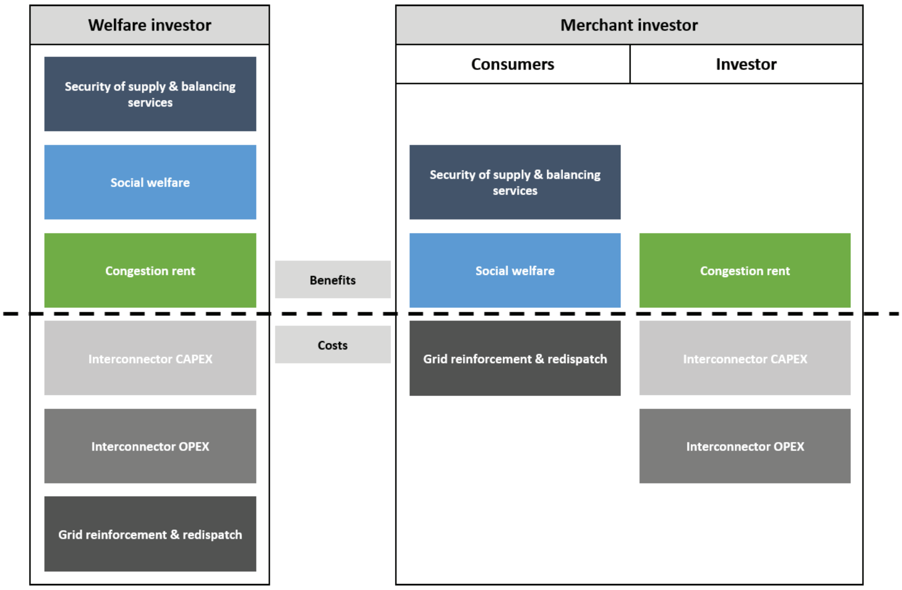


Figure 1.10: General illustration of the cost-benefit difference between a welfare- and merchant investor. For a welfare investor, all costs and benefits are allocated to the society (producers and consumers). On the other hand, a merchant investor will only be exposed to isolated costs and benefits from the infrastructure investment.

1.4 Research objectives

The previous sections provides insights to important aspect for the development of a power system, which is relevant for the research presented in this thesis; on renewable integration and its variable characteristics; flexibility needs to balance variations; the benefits of a strong grid infrastructure; and key considerations for future planning problems. Additionally, the recent push from the EU Commission to stimulate more multinational infrastructure projects (European Commission, 2011; ENTSO-E, 2016) for pan-European trade and resource utilization, calls for adequate decision support tools to help policy makers and other practitioners to get the necessary insights and knowledge.

The work presented in this thesis can be rooted back to three research objectives (ROs):

RO1 Utilize traditional methods for transmission expansion planning and adopt it to a multi-national context.

RO2 Identify challenges and opportunities to enhance decision support for TEP – spanning a methodical-, computational-, and illustrative context.

RO3 Use open-source and transparent data that reflects real case studies (North Sea Offshore Grid).

All with the unified goal of providing better decision support that could help understanding how to maintain a sustainable and cost-efficient development of the power system going forward. Moreover, the numerical examples should be possible to reproduce as a result of using, and providing, open-source data and models.

1.5 Research contributions

During the course of the PhD project, optimization models have been developed to identify optimal system designs. Moreover, methods from other disciplines such as systems engineering and game theory have been used to explore tradeoffs of different system designs and to better understand the cost-benefit allocation problem. In addition to this, statistical methods have been used to reduce the dimensionality of input data to the models. Finally, results are demonstrated with case studies of a North Sea Offshore Grid (NSOG), including the latest vision of using an artificial island in the Doggerbank area exploiting economies of scale (TenneT, 2017b). With this, different aspects of the transmission planning problem has been investigated in face of future development of a NSOG.

The following contributions can be derived from this thesis:

C1 Customized models for multinational TEP in an open source environment, programmed with Python (and the optimization library; Pyomo). Both a deterministic and a stochastic optimization model, generic for multi-stage investment decisions.

C2 Case studies of a future, potential North Sea offshore grid and its impact on surrounding countries using transparent and open-source data for year 2030. Main topics include flexibility needs and the role of interconnectors in market environments with varying shares of renewables (e.g. offshore wind), other flexibility providers (e.g. hydro, storage, gas, demand), artificial offshore wind power hubs (Power Link Island), and uncertainty (e.g. generation mix).

C3 Demonstrated the added value of applying methods from statistics, game theory, and systems engineering. This to reduce model dimensionality, account for bargaining power and estimate the value of efficient/fair payoffs/incentives, and systematically untangle complexities related to alternative solutions and tradeoffs.

All of which are a result of the following publications, listed in chronological order by publication- or completion date:

- Kristiansen, M., Korpås, M., and Härtel, P. (2015). Scenario Robustness and Cost-Benefit Allocation for Multinational Transmission Grid Investments - A North Sea 2030 Case Study. *WIW 2015 Proceedings.*
- Kristiansen, M., Korpås, M., Farahmand, H., Graabak, I., and Härtel, P. (2016). Introducing system flexibility to a multinational transmission expansion planning model. In *19th Power Systems Computation Conference (PSCC'16).*
- Härtel, P., Kristiansen, M., and Korpås, M. (2017). Assessing the impact of sampling and clustering techniques on offshore grid expansion planning. *Energy Procedia.* 14th Deep Sea Offshore Wind R&D Conference, EERA DeepWind'2017, *137*.
- Kristiansen, M., Svendsen, H. G., Korpås, M., and Fleten, S.-E. (2017). Multistage grid investments incorporating uncertainty in offshore wind development. *Energy Procedia.* 14th Deep Sea Offshore Wind R&D Conference, EERA DeepWind'2017, *137*.
- Kristiansen, M., Korpås, M., and Härtel, P. (2017). Sensitivity analysis of sampling and clustering techniques in expansion planning models. *2017 IEEE International Conference on Environment and Electrical Engineering and 2017 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I CPS Europe).*

- Kristiansen, M., Rehn, C. F., Fleten, S.-E., Korpås, M., and Hobbs, B. F. (2017). Rethinking transmission expansion planning: Gaining insights by combining optimization and tradespace exploration. *Submitted to European Journal of Operational Research.*
- Kristiansen, M., Korpås, M., and Svendsen, H. G. (2018). A generic framework for power system flexibility analysis using cooperative game theory. *Applied Energy, 212.*
- Kristiansen, M., Korpås, M., and Farahmand, H. (2018b). Towards a fully integrated North Sea offshore grid: An engineering-economic assessment of a power link island. *Wiley Interdisciplinary Reviews: Energy and Environment.*
- Kristiansen, M., Korpås, M., and Farahmand, H. (2018a). Economic and environmental benefits from integrated power grid infrastructure designs in the North Sea. *Journal of Physics: Conference Series, 1104*(1).
- Kristiansen, M., Muñoz, F. D., Oren, S., and Korpås, M. (2018). A Mechanism for Allocating Benefits and Costs from Transmission Interconnections under Cooperation: A Case Study of the North Sea Offshore Grid. *The Energy Journal, 36*(9).

In addition to relevant master projects that were supervised during the PhD and published through the following conference proceedings:

- Åmellem, L., Kristiansen, M., and Korpås, M. (2016). Incorporation of Flow-Based Grid Modelling in Multinational Transmission Expansion Planning. *WIW 2016 Proceedings.*
- Bjerketvedt, V. S., Kristiansen, M., and Korpaas, M. (2016). Analyzing the investment impact of strategic players with market power. *2016 51st International Universities Power Engineering Conference (UPEC).*
- Risanger, S., Kristiansen, M., Munoz, F., and Korpås, M. (2018). Assessing incentives for multinational cooperation towards a north sea offshore grid using allocation methods from coalitional game theory. *IAEE International Conference 2018.*

And other contributions in joint collaboration between NTNU and Sintef Energy:

- Svendsen, H. G. and Vrana, T. K. (2017). *Economic offshore grid structures and robustness to uncertainties regarding wind power developments.* IRPWind Technical Report.
- Svendsen, H. G., Kristiansen, M., and Korpås, M. (2017). *Step-wise stochastic optimisation of transmission grid for offshore wind farm clusters.* Offshore Wind Energy 2017 conference.

1.6 Thesis structure

Chapter 2 - Research methodology

This chapter provides a framework for the research presented in this thesis. The objective is to augment to the introduction with sufficient information to understand the underlying motivation and different elements being presented in the papers. For this, stylized examples are provided with references that are considered particularly relevant.

Chapter 3 - Contributions

Following the contributions that are outlined in the introduction, this chapter aims to summarize these on a paper-by-paper basis, including main takeaways from each of the articles listed in the previous section.

Chapter 4 - Conclusions

Based on the presented research and results, conclusions are derived in this chapter. Finally, based on insights and ideas that were generated throughout this research, a set of future recommendations is presented.

Chapter 2

Research methodology

> “ ”
>
> Donald Rumsfeld, *There are known knowns. These are things we know that we know. There are known unknowns. That is to say, there are things that we know we don't know. But there are also unknown unknowns. There are things we don't know we don't know.*

Grid expansion and tighter market integration is a prominent way to cope with decarbonization of the power system, enabling larger shares of renewable resources to be included and utilized to its full potential. The North Sea Offshore Grid (NSOG) is a prominent case since it involves multiple countries, a geographically sparse location of renewable resources that are unevenly distributed in the region, no centralized planner, and decentralized incentives for multinational transmission grid projects (ENTSO-E, 2014). In other words, a perfect case for reviewing increasingly important aspects of transmission expansion planning (TEP) such as appropriate modelling techniques, computational challenges, exploration of designs and tradeoffs, conflicting objectives, and incentives for cooperation.

In order to structure the research approach for this thesis, a three-folded breakdown of a typical TEP workflow is proposed, namely:

1. *Pre analytics*: Processing and manipulation of input data.
   - Main disciplines: Statistics and operations research
   - Main tools: Python[1], CPLEX[2], Gurobi[3]
2. *Model development*: Methods and algorithms used to formulate- and solve mathematical optimization models, including different approaches to consider for different types of problems.
   - Main disciplines: Operations research, power systems engineering, energy operation and planning, game theory, project finance, economics, real options theory

1. Python: https://www.python.org/.
2. CPLEX: https://www.ibm.com/products/ilog-cplex-optimization-studio.
3. Gurobi: http://www.gurobi.com/.

- Main tools: Python, Matlab[4], CPLEX, Gurobi, SourceTree (Git GUI)[5]

3. *Post analytics*: Interpretation of model results and application of methods from other fields, such as cooperative game theory or system engineering, that could help gain additional insights.

   - Main disciplines: Operations research, game theory, systems engineering, finance
   - Main tools: Python, Matlab, Tableau

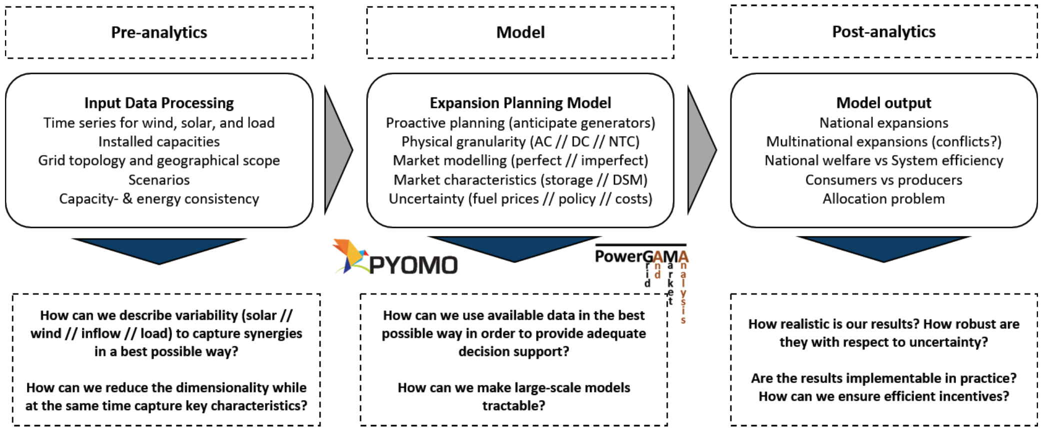


Figure 2.1: The transmission expansion planning divided into preprocessing of data, modelling, and ad-hoc analyses. A streamlined presentation of the context for the research reported in this thesis.

Figure 2.1 shows this breakdown with the first one being related to input data and methods to be used for, e.g. , reducing the size of your data set without loosing significant information or value. The second, modelling part, comprise different views to be considered when modelling an expansion planning model, including solution techniques. Finally, the third part represents everything related to ad-hoc analytics of your model output. All three parts are, as shown later, highly dependent and interlinked. For instance, changes in input data or model will naturally have a considerable impact on the results. Hence, they are all of (equal) importance and should be treated accordingly, making it essential to understand the whole ”TEP workflow” and not just parts of it.

The following subsections will follow this three-folded structure with accompanying introductions and examples to relevant topics. A majority of this material is already presented in the papers, but here in a more structured way.

4. Matlab: https://se.mathworks.com/.
5. SourceTree: https://www.sourcetreeapp.com/.

2.1 Pre analytics

Model development is not only about the model itself but, maybe more importantly, also the acquired data and how it is processed as model input. There are at least four important aspects to consider when applying data to TEP models:

1. *Scenario generation* – establish a data set that represents current- and/or future systems in a realistic way.

2. *Spatial details* – incorporate geographical granularity and characteristics.

3. *Temporal details* – represent appropriate time resolutions that capture variations and interdependencies.

4. *Scale* – the resulting size of the input data and subsequently its impact on the model feasibility.

The first being how good the data reflects reality, and especially when simulating future scenarios for, e.g. , year 2030. Here, public data can be used and validated with a model. For instance, by comparing prices and power flows between the model and actual data provided by the TSO and/or the power market exchange. Spatial details, 2), could involve whether to represent each individual generator, or load, individually or as aggregate elements represented by one, or a few, elements. The latter is also somewhat related to temporal details, 3). That is, whether to represent system dynamics at an hourly or daily scale, and subsequently the number of states (hours or days) to include. The latter is often dependent on the physical nature of the system in question, e.g. for energy storage it might make sense to analyze subsequent states rather than just random states. Finally, the size of the input data, 4), is seemingly a key driver for the complexity and size of the resulting model in which these interactions in both space and time are simulated. Together, these are all quintessential for the ability to quantify value – which in the end is the ultimate goal for TEP.

2.1.1 Scenario generation: North Sea Offshore Grid in 2030

Data is acquired for the purpose of analyzing real life case studies for a future NSOG, although some studies are ran with large-scale pan-European data sets using PowerGAMA (a market simulator for the European power system) (Svendsen & Spro, 2016). Relevant data for the NSOG includes country-wise supply and demand (ENTSO-E, 2014, 2016), hourly supply- and demand characteristics (Staffell & Pfenninger, 2018), fuel costs, capital and operational costs for transmission lines and power electronics (Härtel et al., 2017), financial parameters, and offshore wind data (WindEurope, 2017). To summarize, these are the data sources used:

1. *ENTSO-E*: TYNDP 2014 and 2016 Vision 1-4 for installed generation capacities and peak load levels per country, including hourly load profiles. The same source was used to approximate marginal costs for electricity generation per technology, including CO2 prices.

2. *Wind Europe*: Used to factor in geographical spread of offshore wind capacities (Nghiem & Pineda, 2017) given in 1). Since the newest ENSTO-E TYNDP did not distinguish onshore- and offshore wind, this was used to approximate the offshore wind share.

3. *EU Roadmap 2050*: Capital costs for different generation technologies in year 2030 (European Commission, 2011).

4. *IEA*: CO2 emission rates from fuel combustion highlights 2016 (International Energy Agency, 2016).

5. *Reanalysis*: Hourly time series were generated based on simulations of numerical weather data (Kalnay et al., 1996) with temporal resolution at six hours and spatial resolution at 2.5 degrees (equivalent to 278km), spanning 10 years. This was used for approximating power production from wind, offshore wind, and solar for a given set of coordinates using a model developed by Aigner (2013).

6. *COSMO-EU*: Hourly time series were generated based on simulations of numerical weather data (Schattler, Doms, & Schraff, 2018) with temporal resolution at one hour and spatial resolution at 7km, with wind data from 2005 and solar data from 2011. Also using a simulation model developed by Aigner (2013).

7. *Renewable.Ninja*: A more transparent alternative for hourly time series data than the two options listed above; Reanalysis and COSMO-EU. This database is used as a more accessible open-source alternative for wind- and solar PV (Pfenninger & Staffell, 2016b, 2016a; Staffell & Pfenninger, 2018).

8. *Nordpool*: Hourly price data for Norway (Nord Pool, 2017). These time series are primarily used to model hourly- and seasonal variations for hydropower. That is, by assuming perfect competition one can assume that the spot price is a good approximation for the marginal cost of water (water value).

A majority of the work presented in this thesis is based on data from the European Network of Transmission System Operators for Electricity (ENTSO-E) who provides bi-annual publications on a Ten-Year Network Development Plan (TYNDP), including 2030 scenarios. To this end, four different scenarios (called ”Visions”) are established with the purpose of bridging the gap between European climate- and energy targets for 2020 and 2050 (ENTSO-E, 2016; European Commission, 2011), under different assumptions for the future evolution of the power system. In short, Vision 1 and 4 is the least- and most ambitious scenarios, respectively, with respect to meeting energy- and climate targets. Together mapping a range of possibilities for year 2030, as illustrated in Figure 2.2.

The four scenarios can, in its most simple form, be described with two variables as depicted by the y- and x-axis in the left part of Figure 2.2. First, the y-axis representing the development of renewable energy sources and compliance with the EU Energy Roadmap 2050 aiming at greenhouse gas emission reductions to 80-95% below 1990 levels (European Commission, 2011). Its upper end implies a energy system being on track with the EU Energy Roadmap towards 2050 while at the lower end represent severe deviations from targets, where delays are expected. The x-axis depicts the progress towards a strong or loose European framework facilitating its decarbonization process. Therefore, on this axis a high degree of European integration with a unified approach of setting and achieving goals opposes a low degree of integration without a common vision of Europe’s future energy system and rather separate national approaches.

From a TEP perspective, these scenarios will largely influence the benefits of a set of new transmission projects. For instance, Vision 4 ”Green Revolution” is a future with high levels of variable supply capacity where there likely will be times when price differences between two areas are relatively high, due to low marginal costs and high power feed-in, which justifies capacity arbitrage opportunities for a grid investor. This is an investment signal for more spatial flexibility. In contrast, Vision 1 ”Slow progress” which is a more conservative future with something similar to today’s supply and demand mix might not require the same level of infrastructure investments.

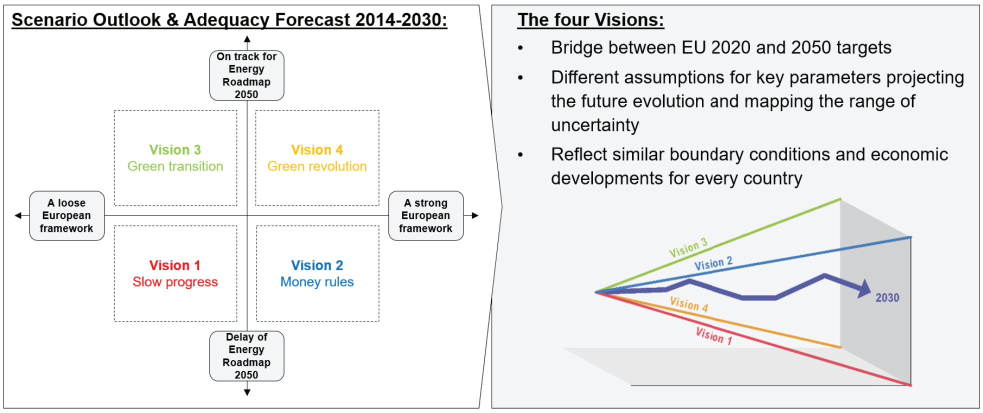


Figure 2.2: ENTOE's four visions for 2030. Ranging from slow-progress to green revolution. These scenarios are used as a basis for all work presented in this thesis. Illustrations from previous work together with Philipp Härtel (Kristiansen, Korpås, & Härtel, 2015; Kristiansen, Korpås, Farahmand, Graabak, & Härtel, 2016).

The merit-order supply curve and the basic expansion planning economics from the Introduction chapter, Figure 1.4 and Figure 1.8, clearly demonstrates this effect, given a competitive market (i.e. price equals marginal costs).

Vision 4 - "Green revolution"

The remainder of this thesis will refer to Vision 4, unless anything else is stated. It is a scenario of particular importance from a strategic planning point of view, considering that it represents a system that is very different from todays'; characterized with a large degree of variability, a high carbon emission price, slightly higher demand as a result of the transport sector being supplied with electricity. Moreover, it is visioned that demand response will emerge, shifting/shaving peak load levels. Nuclear capacity is being phased out in this scenario, mainly due to political outlooks and its inability to meet variations in net load (e.g. from renewables). A summary of this data is provided in Table 2.1 for the North Sea case study.

While ENTSO-E Vision 4 provides an adequate foundation, it has the drawback of aggregating some technologies. For instance, there is no distinction between onshore- and offshore wind capacity. Moreover, the range of efficiency for different technologies is also a bit vague where gas, which represent a majority of the supply capacity, span between 25% and 42%.

Categorization of technologies can also affect the degree of freedom. For instance, users of this data have to decide attributes for "Other RES" and "Other non-RES" – such as fuel costs and capital costs – as a result of limited documentation from ENSTO-E. Consequently, one would have to approximate the capacity and marginal costs of emerging technologies that does not fit into neither categories, which is the case biomass, among others.

Hydropower, which is one of the dominating supply technologies in the Nordic system, comes without any representative marginal costs nor price profiles for 2030. The data providers could add significant value by simulating water value profiles with the same models or systems that are used to generate the official ENTSO-E Visions. However, since this is not the case, price profiles from 2015 (Nord Pool, 2017) are used to represent the seasonal variations for the marginal costs of hydropower. Another alternative could be to use Vision 4 and simulate water values for year

Table 2.1: Input data: Marginal costs, generation capacity and peak load per country (ENTSO-E, 2016). An emission tax of 76 €/tonCO_2 is added on top of marginal costs for thermal generators. The economic lifetime of investments is assumed to be 30 years and the discount rate is 5 %.

	Costs EUR/MWh	NO	DK	DE	NL	BE	GB	Sum
		MW						
Biomass	50	0	1 720	9 340	5 080	2 500	8 420	26 880
Coal	21	0	410	14 940	0	0	0	15 350
Lignite	10	0	0	9 026	0	0	0	9 026
Natural Gas	65	855	3 746	45 059	14 438	10 040	40 726	114 864
Hydro	-	48 700	9	14 505	38	2 226	5 470	70 948
Nuclear	5	0	0	0	486	0	9 022	9 508
Oil	140	0	735	871	0	0	75	1 681
Solar PV	0	0	1 405	58 990	9 700	4 925	11 915	86 935
Wind Onshore	0	1 771	6 695	76 967	5 495	3 518	27 901	122 347
Wind Offshore	0	724	6 130	20 000	4 500	4 000	30 000	65 354
Total generator capacity	-	52 050	20 850	249 698	39 739	27 209	103 510	493 056
Peak load	-	24 468	6 623	81 369	18 751	13 486	59 578	204 275

2030 using a market simulator. Although the latter approach has been investigated by a master student supervised by the author, it has not been implemented and used in the research presented in accompanying papers.

2.1.2 Spatial- and temporal data representation

Spatial resolution refers to the geographical representation of elements in a system. For instance, whether generation units are modelled individually or at an aggregate level. The former results in the highest level of detail, but aggregations could also provide adequate descriptions of its characteristics. It often depends on the scope of the case study and analysis. For a short-term operational analysis it might be essential with high spatial granularity, while for a long-term expansion planning case an aggregation might be sufficient – especially when considering larger geographical areas. This decision would, however, strongly depend on computational challenges in addition to the frequency of analyses.

With respect to the time dimension, we often refer to this as temporal representation. That is, given the nature of a system, what is the appropriate time resolution? Should different time steps (market states) be modelled in sequence, or is it sufficient to select a random subset from a given time interval? The day-ahead spot market is cleared at an hourly basis, which makes hourly resolution quintessential when modelling power systems. However, intra-hour variations are becoming more relevant as smarter demand is emerging (increased price elasticity) and a feed-in of variable supply is increasing (the wind- and sun does not blow- and shine constantly throughout an hour). Hence, intra-day markets could be used to balance deviations from the day-ahead market commitment.

Spatial - geographical level of detail

Most case studies presented in this thesis is based on a relatively low spatial detail, meaning that the location of supply-, demand-, and grid capacity is represented at an aggregate level. This because of three reasons; i) open-source data is usually given at aggregate level (per country), ii), the focus is long-term planning for offshore grids with limited number of HVDC corridors (distributional effect on onshore AC grid is out of scope), and iii), acquiring- and maintaining a

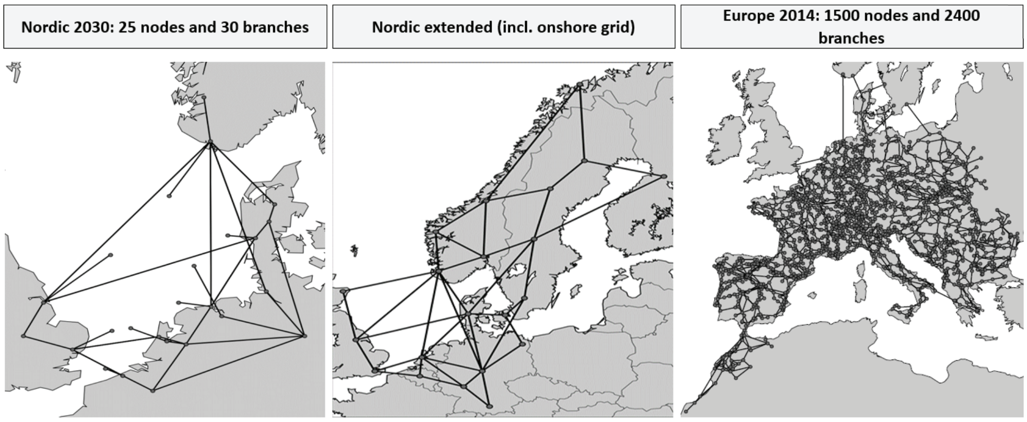


Figure 2.3: Own illustrations of the spatial resolution of data sets that have been available, or developed, for the transmission expansion planning model during the course of this PhD project. These are based on (Trötscher & Korpås, 2011; ENTSO-E, 2016; Svendsen & Spro, 2016).

highly detailed data set requires a lot of work. Also, the case studies are for illustrative proposes and not commercial ones – mainly to show the impact and sensitivities of investigated methods.

Figure 2.3 shows the data sets that have been used throughout the PhD project, with a primary focus around the North Sea Offshore Grid (NSOG). The left part in Figure 2.3 shows the most used case study comprising six countries in total: Norway (NO), Denmark (DK), Germany (DE), The Netherlands (NL), Belgium (BE), and Great Britain (GB). This fits well with the aggregate data sets provided by ENTSO-E for 2030. The idea is to maintain sufficient level of detail in order to represent different countries interlinked by the NSOG, with a simplified representation of domestic onshore grid congestion. To this end, one could still identify the value value of expanded transmission corridors between countries – which is the main objective. The impact of increasing the level of onshore grid details, including load flow equations, is investigated together with a master student in (Åmellem et al., 2016).

The middle map in Figure 2.3 shows a system with slightly higher spatial resolution, replicating the main price areas at Nord Pool Spot (Nord Pool, 2017). Finally, to the most right hand side a highly detailed representation of the European power system is depicted. The latter is based on (Svendsen & Spro, 2016) which recently has been expanded to include Great Britain and Norway (Larrañaga Arregui, 2017), as shown in Figure 2.4.

Temporal - time step granularity

An hourly time resolution is used for all case studies presented here. A majority of the energy in this system is traded at the day-ahead spot market, which then serves as a good basis for estimating future cash flows. Although it is not certain if a market design will remain the same for several decades (a normal horizon is typically 30 years for economic assessments) it is fair to assume that the marginal pricing of resources, through market prices (perfect competition), will give a good representation of system dynamics. For the latter, relative metrics is more important – i.e. low versus high costs, or flexible versus inflexible resources.

In many cases, one could use historical data to collect statistics about a variable – i.e. a generation unit or a load center for a given geographical location. Consequently, this data could

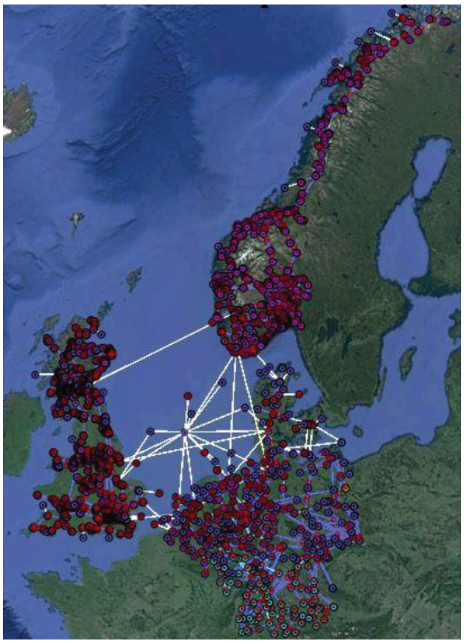
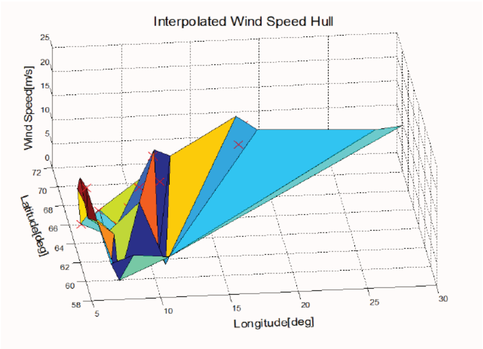


Figure 2.4: Augmented data set to the one showed in the right part of Figure 2.3. Developed by a co-supervised master student (Larrañaga Arregui, 2017). Note that the offshore grid topology depicted here is a result from another investment model (PowerGIM) assessing potential solutions for a "Power Link Island".

also be used to represent uncertainty (stochastics) and variability. However, in some cases there might not exist any historical data. The latter is particularly true for offshore wind farms that are located far from coordinates with historical data (see the nodes/dots located offshore in the left part of Figure 2.3). In such cases, numerical weather data can be used to approximate power generation profiles based on coordinates, surface (water, mountains, or fields), height/elevation (e.g. for wind turbines), or angle (e.g. the tilt of a solar PV) (Aigner, 2013). When the location of certain power generators does not match with the coordinates for the numerical weather data, a lat-lon to wind speed or solar irradiation interpolation could be calculated, as illustrated in Figure 2.5.

Simulating power curves based on numerical weather data is potentially a cumbersome approach and most resources used in this thesis are already developed in a previous PhD project at NTNU (Aigner, 2013). For more information about the power profile model itself, please consult with the aforementioned thesis. There, multiple case studies are ran in order to quantify the accuracy of simulated power curves with examples being the one depicted to the right in Figure 2.5. For that case, it is shown that COSMO EU (red) achieves a correlation coefficient about 0.94 (186 MW MAE) compared to actual TSO data (blue), whereas Reanalysis amounts to 0.85 (331 MW MAE).[6] The latter tends to overestimate the duration of peak- and off-peak hours, compared to COSMO EU, as demonstrated in (Kristiansen et al., 2016) when comparing the two

6. Mean Absolute Error (MAE) is a metric used to determine accuracy of a variable, i.e. how good it fits to original data. In contrast to the Root Mean Squared Error, the MAE does not penalize large deviations to the same extent as RMSE.



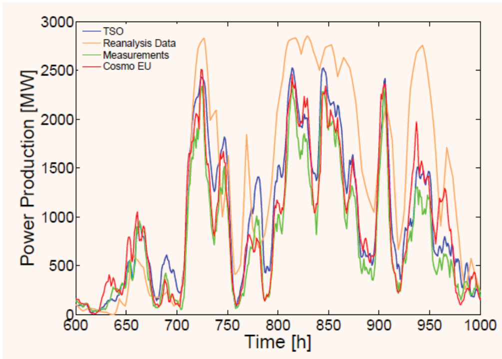


Figure 2.5: Left plot: Coordinates to feed-in interpolation (triangulation). In this case for wind in Norway. Right plot: simulated power curves based on Reanalysis (orange) and COSMO EU (red), compared with benchmark TSO data (blue). Figures from (Aigner, 2013).

with TEP model results.

Lately, multiple open-source databases have become available for users in need of production profiles for a given technology and coordinate. One example is Renewable.Ninja (Pfenninger & Staffell, n.d.), which is an useful source for renewable data in addition to being well documented in, e.g., (Staffell & Pfenninger, 2018).

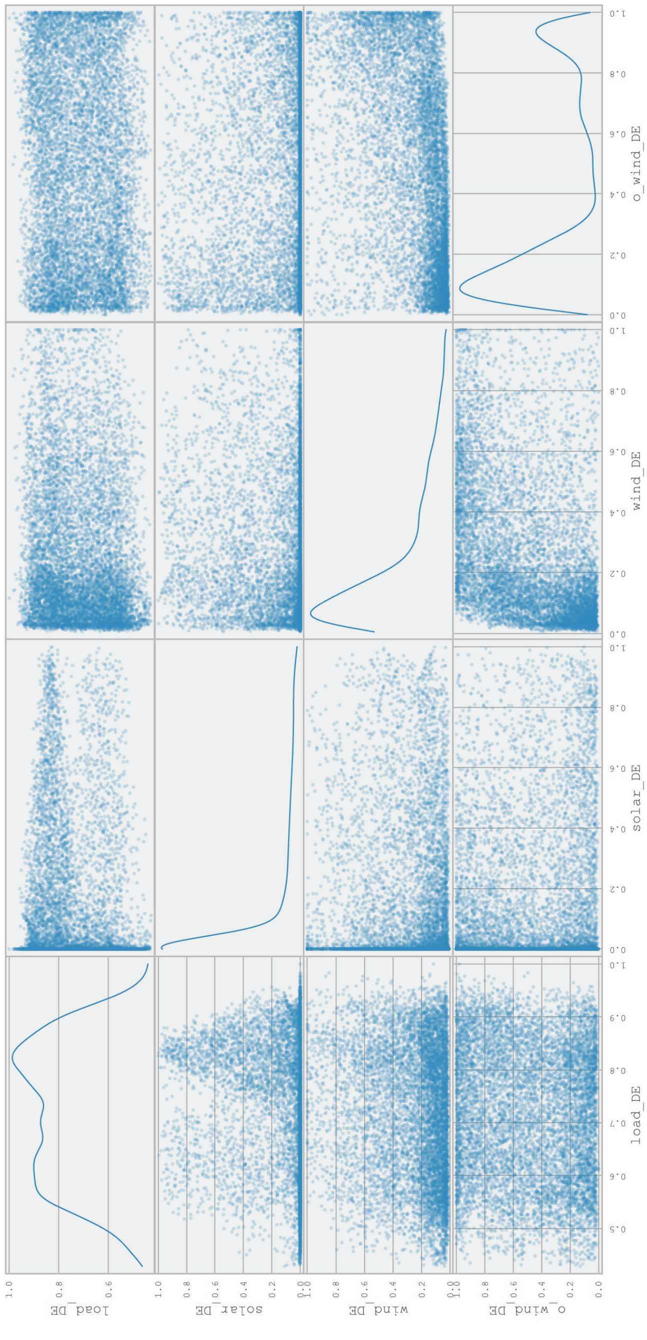


Figure 2.6: A scatter-matrix of one-year, hourly, normalized time series for load, wind, solar pv, and offshore wind in Germany (DE). Data: ENTSO-E Vision 4 (ENTSO-E, 2016).

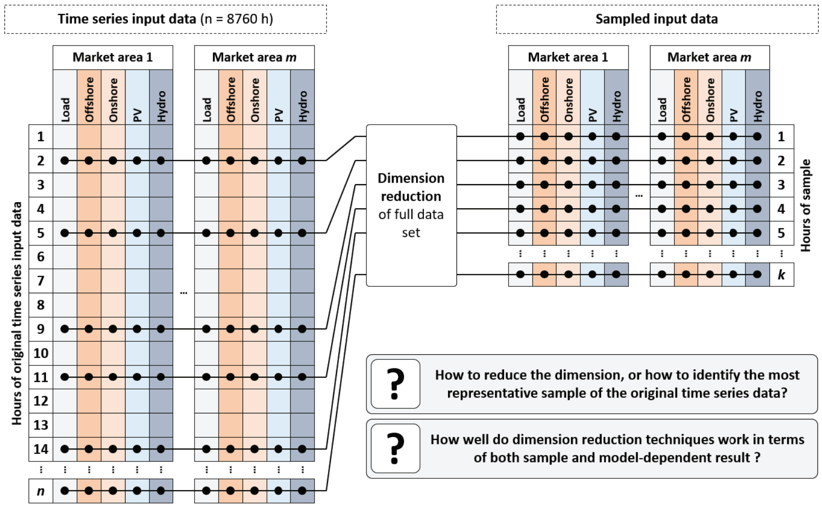


Figure 2.7: Sampling or clustering data allows for dimension reduction (Härtel, Kristiansen, & Korpås, 2017; Kristiansen, Korpås, & Härtel, 2017). This is very useful for model input data with the objective of reducing model size while maintaining the same characteristics of the original input.

2.1.3 Dimension reduction techniques

Once the spatial and temporal data sets are collected and processed, the first problem to encounter for TEP applications is; size. Large data sets results in large optimization programs – and in some cases intractable models. For instance, the right part in Figure 2.3 would be very challenging to solve when considering the option to expand all transmission lines in addition to candidate lines. A high level of spatial and temporal detail would yield a more detailed simulation of operational system dynamics, which in turn is important for capturing underlying value drivers for the investment decisions. That is, an ideal case would be an hourly representation of the interplay between the supply- and demand at the highest level of detail possible – typically for all 8760 hours over a year. Figure 2.6 illustrates this interplay with a scatter matrix for German load, solar PV, wind, and offshore wind at an hourly resolution. Ideally, all possible correlations of this data has to be simulated in order to reflect normal and extreme combinations of different elements.

These dimensions could in many cases be reduced by a considerable fraction while still maintaining good descriptions of the main characteristics. Figure 2.7 illustrates the concept of sampling or clustering of data from a full data set (left) to a reduced one (right). The data might comprise multiple market areas and technologies with records spanning several thousand data points (in this case 8760 hours). Given that the left part best represents the system at hand, it is also the best basis for quantifying their interplay in a modelled system. Hence, in order to capture the true underlying values in a system, it is important to maintain the best possible characteristics.

Focusing on ways to reduce the dimensionality of input data, several methods have been applied in this thesis. Primarily methods from statistical learning. A summary is provided below.

1. Systematic sampling

2. k-means clustering

3. k-medoids clustering

4. Hierarchical clustering

5. Moment-matching

6. (Model dependent sampling)

Systematic sampling is based on simple rules that, e.g. , selects every time step with a given interval. Here, it is important to consider the impact of phase shifting the whole sequence of selected values. For instance, instead of starting with hour one and selecting every next 100 hours, what happens if the first data point is hour two, and so on till the second value is reached in the sequence when starting in hour one. K-means and k-medoids are two well known clustering techniques from unsupervised machine learning. The primary goal with those is to select a number of categories, or groups, and the find the most representative values for those groups. The main difference between the two is that k-means selects the mean value of a group of data points, whereas the k-medoids selects the closest real data point to this mean center.

Hierarchical clustering is based on building an hierarchy of clusters – either bottom-up (agglomerative) or top-down (divisive). The former approach is used in this thesis, meaning that each point in the data set starts off as a cluster which later is being merged with other clusters. The algorithm can rely different distance metrics, but for the work presented in this thesis an Euclidean distance is used to assess the proximity of clusters' centroids and mean values, which is the linking criteria. The second last method, moment matching, is simply an algorithm that minimize the statistical moments between a subset (sample) of data and the full data set. For instance, minimize the deviations in mean and variance. To this end, the goal is to achieve about the same statistical metrics as the full data set. Each subset is typically a random sample of the full data set, and one would need at least 10000 such subsets in order for the method to provide a robust solution (van der Weijde & Hobbs, 2011).

The aforementioned methods are all good ways to cope with dimension reduction. However, it is important to understand the main value drivers in the model where those reduced data sets are being applied. For instance, by over-representing data points that are closer to their mean than their extremes, one might not capture the most extreme price differences in a power system. That is why model dependent sampling is included to the above assertions. Meaning that the model in question in being included in the process of selecting a reduced data set. Although this is not always possible, and often the reason why we need dimension reduction techniques, it is an important aspect to keep in mind. Although this is not investigated in this research, two examples for model dependent sampling could be:

- Run an optimization model and retain the cost vector for all hours. Rank hours based on cost-importance.

- Use the same cost vector above and link it with the input data performing a principal component analysis, which would help to identify which loads/technologies that explains the most variance in the cost vector.

Performance metrics for dimension reduction

As briefly discussed, there are two common ways to quantify the performance of sampling and clustering techniques:

1. Model independent: Compare statistical metrics between full- and reduced data sets (left vs right in Figure 2.7).

2. Model dependent: Compare TEP model output based on full- and reduced data set.

The first approach will capture statistical moments that, e.g. , tells something about how well the input data is replicated with a reduced data set. For instance, whether the same mean and standard deviation is maintained. However, there might be other aspects that are more important for expansion planning models. For instance, transmission investments are naturally driven by price deviations between two adjacent areas. The larger the price difference, the stronger the investment signal for more transmission capacity. Hence, it might be relevant to capture ”extreme” hours rather than ”normal” hours. This is exactly what assertion number two above reveals, hence also the preferred method for assessing model dependencies.

The robustness of different dimension reduction techniques could simply be measured by varying parameters in a model (Kristiansen et al., 2017). Preferably parameters that are not directly related to the selection process of a subset of data points. For instance, a variation of available capacities for different generation technologies might also affect the derived subset of data points. However, other parameters such as discount rate or economic lifetime should not affect the latter given a model independent sampling or clustering.

2.2 Model development

There are many ways to develop an expansion planning model. First, there are some fundamental aspects that lays the framework for the rest. For instance, how to replicate a system (of systems) and its dynamics? What is the ultimate goal for the decision maker, or planner? Who are the stakeholders and how do they respond to these decisions, or changes? What risk attitude do they have? What are their objectives? Are there any dominant players in the market that might tilt its design towards an imperfect market, rather than a fully efficient and perfect market? Capturing strategic dynamics on top of operational ones are usually more challenging than a vanilla perfect competition, price-inelastic demand, copper-plate model. Literature on expansion planning in its different forms is extensive including, e.g. , (Munoz et al., 2012; Lumbreras & Ramos, 2016; Gorenstein Dedecca & Hakvoort, 2016).

Although the process of developing a model extends far beyond different ways to mathematically formulate one, the scope for this section is to overview central aspects. To this end, aspects that are being discussed in accompanying articles to this thesis.

2.2.1 Key considerations

Beyond modelling the system itself, i.e. where different loads and generators are located and at what level those are aggregated and interconnected through an infrastructure, there are additional considerations that are of particular importance. This section will focus on the latter, as the former is somewhat related to acquiring data as discussed in the previous sub chapter. The following assertions are envisaged to be important for TEP planning:

- Static system details - i.e. temporal and spatial representation of different components (e.g. loads, generators and infrastructure).
- Dynamic system representation - capturing how the system responds through interaction of its components (e.g. load flow, ramp rates and losses).
- Market design - representing how participants behave and respond to each others' operational decisions (e.g. imperfect versus perfect competition).
- Proactive investors - strategic decisions that are derived from anticipating other long-term decisions (e.g. bi-level Stackelberg games).
- Forward looking investors - incorporating the chances for unexpected events, variability or technological innovation (i.e. optimization under uncertainty).

These are all related to system dynamics - whether it is between physical components and/or behaviour among participating stakeholders. By systematically untangling theses aspect one could extract insights such as:

- Understanding the system dynamics and needs.
- Assessing the impact of different market designs.
- Assessing incentives for strategic behaviour and its potential impact.
- Quantify value of perfect information and managerial flexibility in face of uncertainty.
- Design incentives for an efficient power system operation and development.

- Explore tradeoffs between different market- and system designs.

The last assertions listed above is rather philosophical and could be classified as an integral part of both model development and post analytics (next section). In the following, the non-technical elements are put in context.

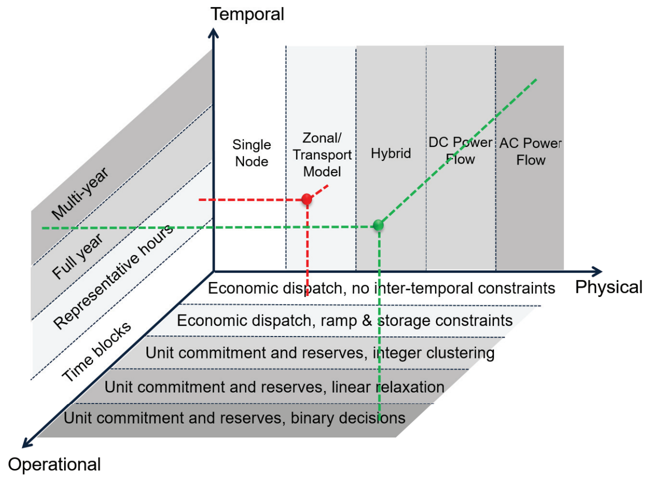


Figure 2.8: System dynamics broken into different levels of granularity for operational details. The red dot represents the level of detail in a majority of planning models, while the green one is at the point with the highest level of details. Figure adopted from (Jesse Jenkins & Nestor Sepulveda, 2017) with modifications.

System representation

Both static- and dynamic system representation does somewhat relate to the Pre Analytics section. That is, deciding the geographical boundaries, level of aggregation, granularity of system infrastructure and temporal resolution. Moreover, component specific characteristics like minimum generating capacity levels, ramp up and -down rates, thermal capacities, AC vs DC lines, will all have an impact on system dynamics.[7]

For transmission expansion planning in the North Sea region, the main drivers for grid investments will primarily be driven by aggregate price levels in each country. Also, in context of infrastructure technology the most prominent choice is HVDC due to a tradeoff in losses and costs that is in favour for DC over long distances. The high voltage part is more related to the theoretical relationship between resistance and current, with the latter being squared and proportional to voltage - with the objective to minimize the current, and maximize voltage, in order to avoid losses. The underlying price signals and DC dominated grid allows for aggregate modelling of each country and load flow equations less dependent on Kirchhoff's voltage law. This is, however, quintessential for AC grids.

The impact of load flow modelling and more detailed domestic grids where assessed using power transfer distribution factors (PTDFs) in a master thesis supervised by the author. It was shown that investments in multinational infrastructure increased as a result of flow based

7. Alternating Current (AC) and Direct Current (DC).

modelling (Åmellem et al., 2016). Also, Norway went from only providing balancing power to the Continent, to also acting as a transportation hub between Great Britain and the Continent as a result of domestic loop flows. Observations like these is of importance when assessing the distributional effects of multinational transmission expansion, i.e. the iduced need for domestic grid utilization and upgrades.

Figure 2.8 provides an illustration of what concerns ”firm system representation”, including data granularity, power flow modelling, and unit commitment. To this end, the green dot represents the ultimate replication of a real system, whereas some models are expected to be located closer to the red dot.

Market design

Market design encompass the purpose of modelling operational behaviour among participants in the system. A market with one player would result in a monopoly, whereas a market with many players would imply perfect competition. Of course, participants could game each other by strategically bidding quantity or price (Cournot or Bertrand games), but a sequential game will ultimately result in perfect competition given the high number of players. The two market forms represents two extremes, the former with high prices and high producer surplus, and the latter with low prices and higher consumer surplus. Everything in between could be viewed as imperfect competition (W. W. Hogan, 1999a). From economics, it is well know that perfect competition, i.e. more goods and services, is positive for welfare surplus. Despite a handful of large players in the Nordic power market, it stands to reason to believe that the day-ahead market operates close to perfect competition and consequently that producers bids at marginal costs.

Different market designs were investigated in a master thesis supervised by the author (Bjerketvedt et al., 2016). From a perspective of an expansion planner, or investor, it was shown that imperfect competition lead to less capacity expansion in order to maintain high market prices, and consequently high profits. The main takeaway is that expansion models based on perfect competition will likely over-invest, compared to what would occur if markets were slightly more imperfect.

A transmission infrastructure is a natural monopoly that is utilized by both parts of what sums to national welfare, namely producers and consumers. Hence, the planning problem is usually viewed from a social welfare maximizing perspective, although an increasing share of merchant (profit maximizing) investors have been observed the last decade - particularly for multinational projects (Doorman & Frøystad, 2013).

Proactive planning

Costs associated with grid investments comes with lumpy and up-front capital intensive characteristics in addition to illiquid re-sale potential (sunk costs). Moreover, its impact on system dynamics and electricity prices can be significant and lead to arbitrage opportunities. To this end, generators might act opportunistic and utilize price changes that result from grid investments. A proactive transmission planner would try to anticipate this, in contrast to reactive planning.

The combination of generation and transmission expansion planning (GTEP) is thus very important (Guerra, Tejada, & Reklaitis, 2016; Alayo et al., 2017; Spyrou, Ho, Hobbs, Johnson, & McCalley, 2017a). For instance, access to infrastructure might drive additional generation investments and siting. Although generators represent profit maximizing entities, it has been shown that a decoupling of the two different planning problems, as a bi-level equilibrium problem, can be recast as a co-optimization problem maximizing welfare (in line with a TSO's objective) (Samuelson, 1952; van der Weijde & Hobbs, 2012). This under the assumption of inelastic demand and many generation companies (i.e. perfect competition).

Forward-looking planning

Short- and long-term uncertainty poses significant challenges for the planning problem. In the short run, blackouts might occur, highly variable supply, and unpredictable weather (Staffell & Pfenninger, 2018). Whereas innovation and investment costs, interest rates, fuel prices, and policy might be difficult to account for in the long run (Hobbs, Kasina, et al., 2016). From a planning perspective, the value of hedging against uncertainty by making robust decisions that are simulated for a range of possible scenarios could be significant (Munoz et al., 2014; Hobbs, Xu, et al., 2016). This is what a forward-looking investor would do.

By endogenously incorporating uncertainty into a planning model the costs associated with the risk of different scenarios will be revealed. The impact of doing so is referred to the value of a stochastic solution (VSS), which is always greater than, or equal to, zero (Birge & Louveaux, 2011). Hence, one could say that it adds an hedging value to the decision maker. In some cases, an optimal portfolio from a stochastic solution might differ significantly compared to all possible deterministic scenarios.

Managerial flexibility

The level of variability and uncertainty caused by current and future market landscapes, in addition to the complexity of planning models, means that an investor has an array of options to consider. Other than making the right decisions on siting, capacity and technology, the value of incorporating the dimension of timing can be significant (van der Weijde & Hobbs, 2012; Munoz et al., 2015; Henao, Sauma, Reyes, & Gonzalez, 2017). That is, understanding the value of postponing decisions, expand investments, impede decisions, or similar, as new information is learned. Moreover, slicing capacity investments into multiple steps to exploit modular characteristics.

Strategic gaming

As novel planning problems span multiple regions or countries it is not surprising that those stakeholders will have different views on what concerns a beneficial decision. That is, each agent can be represented by its own optimization program which, in many cases, yields hierarchical optimization. In literature, this is known as bi-level programming if there is two levels to be optimized – e.g. one for market clearing and one for expansion planning (Pozo, Sauma, & Contreras, 2017). For multinational expansion planning there is often three layers to be considered; multinational transmission expansion planning, national expansion planning, and market clearing (Huppmann & Egerer, 2015).

Assessing different degrees of gaming could add insights and be useful in terms of designing energy policies.

2.2.2 Deterministic model

The transmission expansion planning model presented here is structured as a proactive planning model, meaning that it anticipates optimal generation expansion that results from transmission investments. Hence, a suitable naming would be generation and transmission expansion planning (GTEP). The model is open-source and can be found at a BitBucket website called PowerGAMA

- which is short for Power Grid and Market Analysis. The latter is a market simulator (Svendsen & Spro, 2016). For sake of consistency, the expansion planning model goes under the name PowerGIM - Power Grid Investment Model.

PowerGIM

In its most simple form, PowerGIM is structured in the following way:

- Minimize total costs of:
  - **Investments**: Mainly transmission capacity expansion, but one can also incorporate generation capacity expansion, together yielding a Generation Transmission Expansion Planning model (GTEP).
  - **Market Operation**: Myopic costs for generation, emissions, and load shedding during one representative year with hourly resolution. This ensures that the most cost-efficient resources are utilized at their marginal costs (i.e. generators do not bid strategical).
- Subject to:
  - **Energy Balance**: Supply has to meet demand at all hours during a year. However, load can be curtailed at the cost of VOLL €$/MWh$. Besides local supply and demand, one could export or import to neighbouring, connected nodes.
  - **Maximum generation limits**: Existing and new generation has to comply with physical limitations and available resources. For instance, it cannot exceed its maximum capacity. Also, seasonal and hourly variability of hydro, wind, and solar is factored into the maximum capacity limits in order to capture their interdependencies in the system. This will reveal a variety of power flow routing and geographical flexibility needs, which consequently represent value drivers for grid expansion.
  - **Thermal limits**: Existing and new transmission lines have to operate withing thermal limitations, i.e. equivalent capacity limitations for power flow.
  - **Discrete investment decisions**: Binary variables are used to determine whether a node needs to be built, or not. Depending on whether the node is located offshore or onshore, this variable is used to i) determine costs for relevant power electronics and transformers, and ii), determine whether a transmission line could be connected, or not. Moreover, integer variables is used to determine the number of bulky capacity levels for transmission lines in order to reflect appropriate costs of scale (see e.g. (Trötscher & Korpås, 2011; Härtel et al., 2017).

The GTEP model is based on an extension of the planning models in (Trötscher & Korpås, 2011) and more recently (Kristiansen et al., 2018), which is available online in the same git repository as a pan-European market simulator; PowerGAMA (Svendsen & Spro, 2016). A list of notations for the GTEP model can be found in Table 2.2.

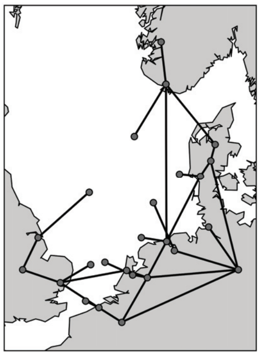


Figure 2.9: Base case for North Sea grid infrastructure (year 2016). Demand and generation capacities are given for year 2030 (ENTSO-E, 2014).

Table 2.2: Notation for the generation and transmission planning model (PowerGIM).

Sets & Mappings	
$n \in N$	: nodes
$i \in G$	: generators
$b \in B$	: branches
$l \in L$	: loads, demand, consumers
$t \in T$	: time steps, hour
$i \in G_n, l \in L_n$	: generators/load at node n
$n \in B_n^{in}, B_n^{out}$	: branch in/out at node n
$n(i), n(l)$	: node mapping to generator i/load unit l
Parameters	
a	: annuity factor
ω_t	: weighting factor for hour t (number of hours in a sample/cluster) [h]
$VOLL$	: value of lost load (cost of load shedding) [€/MWh]
MC_i	: marginal cost of generation, generator i [€/MWh]
$CO2_i$	: CO_2 emission costs, generator i [€/MWh]
D_{lt}	: demand at load l, hour t [MW]
B, B^d, B^{dp}	: branch mobilization, fixed- and variable cost [€,€/km,€/kmMW]
CS_b, CS_b^p	: onshore/offshore switchgear (fixed and variable cost), branch b [€,€/MW]
CX_i	: capital cost for generator capacity, generator i [€/MW]
CZ_n	: onshore/offshore node costs (e.g. platform costs), node n [€]
P_i^e	: existing generation capacity, generator i [MW]
γ_{it}	: factor for available generator capacity, generator i, hour t
P_b^e	: existing branch capacity, branch b [MW]
$P_b^{n,max}$	: maximum new branch capacity, branch b [MW]
D_b	: distance/length, branch b [km]
l_b	: transmission losses (fixed + variable w.r.t. distance), branch b
E_i	: yearly disposable energy (e.g. energy storage), generator i [MWh]
M	: a sufficiently large number
Primal variables	
y_b^{num}	: number of new transmission lines/cables, branch b
y_b^{cap}	: new transmission capacity, branch b [MW]
z_n	: new platform/station, node n
x_i	: new generation capacity, generator i [MW]
g_{it}	: power generation dispatch, generator i, hour t [MW]
f_{bt}	: power flow, branch b, hour t [MW]
s_{nt}	: load shedding, node n, hour t [MW]

The mathematical formulation, (1a)-(1k), is adapted to the 25-bus NSOG case study comprising six countries in total, namely; Norway (NO), Denmark (DK), Germany (DE), The Netherlands (NL), Belgium (BE), and Great Britain (GB), as depicted in Figure 2.9.

The GTEP model is targeted for system characteristics in the North Sea region where both offshore grid technology costs and hydro representation plays an important role. Equations (1d) and (1e) represents the fixed- and variable cost functions, respectively, incorporating distance and power rating, denoted d and p, in addition to end-point switch-gear costs, CS. The fixed costs, C_b^{fix}, are multiplied with the number of new cables, y_b^{num}, and the variable costs, C_b^{var}, with the accumulated new cable capacity, y_b^{cap}, as shown by (1b). Moreover, in cases where new nodes, e.g. offshore platforms, needs to be installed a binary variable is used, z_n, which is enforced by new cables connected to this node (1k). Finally, generation expansion is represented by continuous variables, x_i, which all together with operational variables for generation, g_{it}, branch flow, f_{bt}, and load shedding, s_{nt}, yield a mixed-integer linear program (MILP).

$$\min_{x,y,z,g,f,s} \quad IC + a \cdot OC \tag{2.1a}$$

where

$$IC = \sum_{b \in B} (C_b^{fix} y_b^{num} + C_b^{var} y_b^{cap}) + \sum_{n \in N} CZ_n z_n + \sum_{i \in G} CX_i x_i \tag{2.1b}$$

$$OC = \sum_{t \in T} \omega_t (\sum_{i \in G} (MC_i + CO2_i) g_{it} + \sum_{n \in N} VOLL s_{nt}) \tag{2.1c}$$

$$C_b^{fix} = B + B^d D_b + 2CS_b \qquad \forall b \in B \tag{2.1d}$$

$$C_b^{var} = B^{dp} D_b + 2CS_b^p \qquad \forall b \in B \tag{2.1e}$$

subject to

$$\sum_{i \in G_n} g_{it} + \sum_{b \in B_n^{in}} f_{bt}(1 - l_b) - \sum_{b \in B_n^{out}} f_{bt} + s_{nt} = \sum_{l \in L_n} D_{lt} \qquad \forall n, t \in N, T \tag{2.1f}$$

$$P_i^{min} \leq g_{it} \leq \gamma_{it}(P_i^e + x_i) \qquad \forall i, t \in G, T \tag{2.1g}$$

$$\sum_{t \in T} \omega_t g_{it} \leq E_i \qquad \forall i \in G \tag{2.1h}$$

$$-(P_b^e + y_b^{cap}) \leq f_{bt} \leq (P_b^e + y_b^{cap}) \qquad \forall b, t \in B, T \tag{2.1i}$$

$$y_b^{cap} \leq P_b^{n,max} y_b^{num} \qquad \forall b \in B \tag{2.1j}$$

$$\sum_{b \in B_n} y_b^{num} \leq M z_n \qquad \forall n \in N \tag{2.1k}$$

$$x_i, y_b^{cap}, g_{it}, s_{nt} \in R^+, \quad f_{bt} \in R, \quad y_b^{num} \in Z^+, \quad z_n \in \{0,1\}$$

Kirchhoff's voltage law (KVL) is ignored since a majority of the system infrastructure consists of high voltage direct current (HVDC), i.e. fully controllable transmission corridors. This results in a transport model with no loop-flows (1i). However, linear losses are incorporated to reflect both the transmission distance and use of necessary voltage transformers and power electronics, as seen from the nodal energy balance (1f), i.e. Kirchhoff's current law (KCL). The nodal energy balance (1f) ensures that demand is met by the sum of generation, power flow, and/or load shedding, in each country. Hence, input data is given at national level using a discount rate amounting to 5% and an economic lifetime spanning 30 years (ENTSO-E, 2014).

The variability of wind, solar, hydropower, and load is incorporated using full-year, hourly profiles from both historical data and numerical weather data, where the latter source is particularly relevant for offshore coordinates with limited historical data (Kristiansen et al., 2016). As discussed in the Pre Analytics section. The hourly profiles are reflected in (1g) with a factor, γ_{it}, ranging from 0 to 1 inflow/availability and multiplied with the maximum existing capacity, P_i^e, plus any additional capacity investments, x_i. As part of the Pre Analytics, agglomerative hierarchical clustering is used in order to reduce the hourly time series from 8760 hours to $8760/2^4 = 548$ hours, while still maintaining a relatively high level of multivariate correlations between the time series and between the different geographical coordinates (Härtel et al., 2017; Kristiansen et al., 2017). This improves the models ability to capture underlying values of smoothing effects and variable flow patterns at system level, as discussed in the Introduction.

This model originates from a bi-level structure where generators respond to transmission investments. Due to assumptions of perfect competition, inelastic demand and a welfare maximizing transmission infrastructure investor, one could recast this bi-level equilibrium model as an optimization program that co-optimize both investment- (IC) and operational costs (OC) (Samuelson, 1952). In turn, it is assumed that investment costs (1b) and market operation (1c) reach cost-efficient equilibrium by minimizing the net present value (NPV) of total system costs (1a) measured in €. Operational costs are calculated for one representative year, multiplied with an annuity factor a in order to convert annual costs to NPV.

2.2.3 Stochastic model

Multiple studies have investigated the added value of different model enhancements. For instance, the value of representing more detailed unit commitment, spatial granularity, temporal granularity, network / load flow representation, proactive versus reactive planning, and uncertainty. Xu and Hobbs presents a review on many of those studies and concludes that incorporation of uncertainty adds the most value to the transmission expansion planning problem (Xu & Hobbs, 2018). This is supported by their own results quantifying the value of model enhancements (VOME) representing as much as 26% of the overall benefits of expanding the network. To this end, planning deterministically for the wrong scenario can result in considerable economic regret, compared to the benefits of, e.g. , improving load flow equations. Although this is very model specific (e.g. on region, technology mix, etc.) it is a matter of importance, considering the lumpy and capital intensive nature of grid investments.

In the following sections, a stochastic formulation of the deterministic equivalent is presented.

Scenario tree

Many stochastic programs are based on an underlying scenario tree. That is, a discretized representation of nodes to which decisions are taken based on different stages that spans from root node to leaf nodes (upper- to lower part of Figure 2.10). A given path from a root node to a leaf node is called a scenario. Typically, these nodes are presented in a *topological ordering* $\sigma(\mathcal{T})$ where each parent node u is ordered before its child node v, comprising an edge (u, v). In other words, a node n is always visited after its ancestor nodes on a given path $\mathcal{P}(n)$. The product of all conditional probabilities at this path yields the probability of that scenario to occur. Notations using $n \in \mathcal{T}$ does therefore imply that nodes are visited in ordering $\sigma(\mathcal{T})$.

A standard scenario tree is constructed with respect to both short- and long term uncertainty over a given scenario, i.e. they are both coupled with respect to time. An illustration is given in e.g. Figure 2.10 (c) where a sampled scenario from one of the leaf nodes is coupled through both strategic and operational stages, i.e. both time horizons. However, it is possible to decouple strategic and operational stages if it is reasonable to assume that the two are independent of each other. The equivalent of Figure 2.10 (c) would in this case be Figure 2.11 (b). For

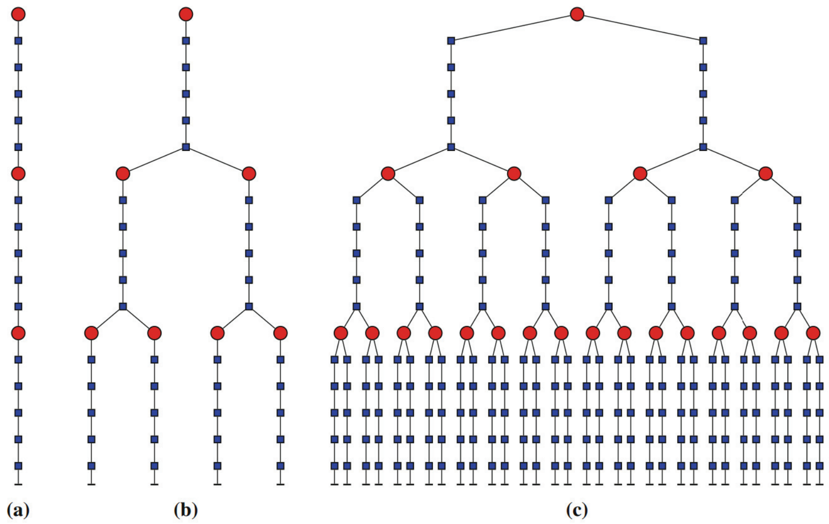


Figure 2.10: Standard scenario trees for a deterministic model (a), a model with strategic uncertainty (b), and a model with both strategic and operational uncertainty (c) (Kaut et al., 2014). Recall that each arc from a branching "sees" the same information, i.e. new information is received at each branching.

long-term planning problems the latter option could be a good approximation with significant computational advantages (Kaut et al., 2014).

The operational time scale is hourly and its values are given by a representative year, i.e. 8760 hours (or a sampled sub set). Operational data comprise multiple timeseries describing a certain spatial- and temporal mix of supply and demand. This allows short-term variability and system dynamics to be properly accounted for, even when sampling only a fraction of the full-year data – which is a rather common approach (Härtel et al., 2017). These operational states could either be incorporated as a second stage in each strategic node (see Figure 2.11 (b)), or it can be represented in deterministic fashion (see Figure 2.11 (a)).

Stochastic optimization model

From the deterministic model already presented, in combination with the scenario tree structure, one could derive the following types of optimization models:

1. Multistage deterministic model.
2. Two-stage stochastic program.
3. Multistage stochastic program.
4. Multi-horizon multistage stochastic program.

The first model is aimed at optimizing investments for multiple timesteps. For instance, whether to do any strategic decisions every five year. Here, the only factor that would distinct strategic decisions across time is discount rate since everything about the future is assumed

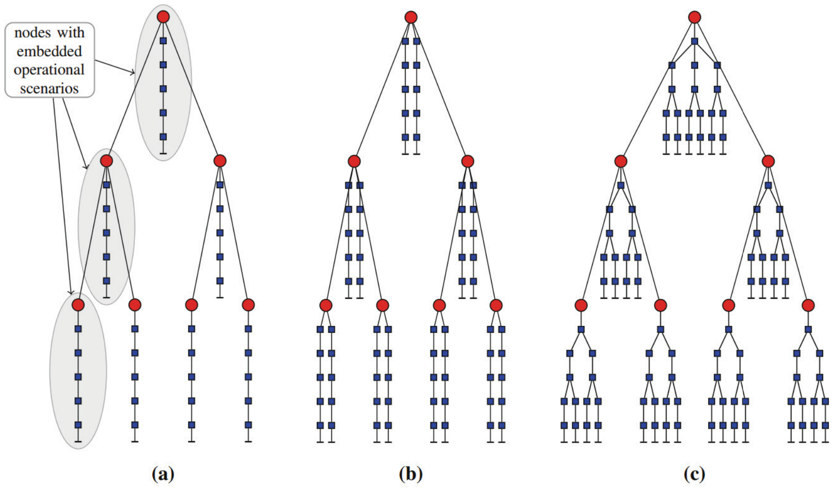


Figure 2.11: Multi-horizon scenario trees with one ST scenario embedded in (a), multiple ST scenarios (b), and stochastic multistage ST scenarios (c) (Kaut et al., 2014). Multi-horizon scenario three (b) is the equivalent for standard scenario tree (c) in Figure 2.10.

known. Contrary, the second model poses strategic decisions clouded by uncertainty going forward. Here, decisions will be driven by both discounting factors (net present value) and uncertainty (information about future cash flows). The third model includes the possibility to postpone decisions in order to learn more information about the future. Hence, an additional value element called "option value" is added to the decision problem. The last model is similar to the forth, but leveraging the fact that long- and short term decisions are decoupled.

From this, one could quantify i) the value of incorporating uncertainty, and ii), the value of managerial flexibility (option to postpone decisions). Thus, possible analyses include:

- Value of Stochastic Solution (VSS). Comparing the recourse solutions with the best deterministic guesstimates about the future (EEV).
- Value of Multistage Stochastic Solution (VMS). Often measured in relative terms to a two-stage solution (RVMS).
- Real option value (ROV). The value of managerial flexibility, i.e. allowing for multiple decisions over time exploiting options concerning modularity, abandonment or new investments.
- Study structural aspects of multistage SP such as number of stages, branches, and scenarios.
- Compare scenario tree structures (multi-horizon versus standard trees)

Some of these metrics are discussed in (Kristiansen, Svendsen, et al., 2017), but for a more comprehensive review on this matter it is recommended to consult with (Huang & Ahmed, 2009) and (Escudero, Garín, Merino, & Pérez, 2007).

The following model is a compact two-stage stochastic representation of the deterministic model in Subsection 2.2.2. The objective function in Equation (2.5a) is divided into two stages;

first the costs related to infrastructure investments, x, and second, the expected costs related to market operations in phase one, $y_1(\omega)$, compensating infrastructure investments, $y_2(\omega)$, and market operation of the remaining analysis period, $y_3(\omega)$, dependent on a discrete set of scenarios, Ω. Note that the infrastructure investments consists of both block-capacity (integer variables x_1) and variable capacity (continuous variables x_2).

$$TC = \min_{x} c^T x + E_{\xi}[\min_{y(\omega)} q^T y(\omega)] \tag{2.2a}$$

s.t.

$$Ax \leq b \tag{2.2b}$$

$$T(\omega)x + Wy(\omega) \leq h(\omega), \quad \forall \omega \in \Omega \tag{2.2c}$$

$$x = (x_1, x_2) \geq 0, x_1 \in Z^+, x_2 \in R^+, y(\omega) = (y_1(\omega), y_2(\omega), y_3(\omega)) \geq 0, y_1(\omega) \in Z^+ \quad \forall \omega \in \Omega$$

The vectors and matrices c, b, and A in Equations (2.5a) and (2.5b) are associated with the first stage variables, i.e. investment in grid infrastructure. The cost vector c is for both fixed and variable node- and branch costs, although node costs may not be relevant in all cases. Vector b restricts the first stage variables, e.g. by maximum allowed capacity per investment block (e.g. 1000 MW per branch), and A is the corresponding coefficient matrix to those investment constraints. The cost vector q is equivalent to c, but it includes marginal costs of generation, emission costs, and value of lost load (VOLL) which is multiplied with market operation in phase one and two, and discounted accordingly back to present values.

The second stage parameters depend on the realization of $\omega \in \Omega$, i.e. the parameters are not quantified before uncertainty is revealed. The sequence of investment- and operational decisions are predefined in the sense that operational decisions respond to investment decisions, given a certain event between the two time steps. That is, one would get the following sequence of decisions and events:

$$x \rightarrow \xi(\omega) \rightarrow y(\omega, x) \tag{2.3}$$

The right-hand-side vector in (2.5c), $h(\omega)$, restricts decision variables in scenario ω, i.e. relevant constraints on market dispatch and second stage operation and/or investments. The *transition matrix*, $T(\omega)$, is associated with first stage variables and can be interpreted in the right hand side restriction together with $h(\omega)$. The transition matrix contains scenario and/or time-dependent data that affects operation in second stage. The recourse matrix, W, is considered fixed in this model since the coefficients in the matrix are independent of the realization of ω.

As an alternative to the compact formulation above, one could use other generic formulations that align with the scenario tree structure, as discussed in e.g. (Ahmed, King, & Parija, 2003; Jin, Ryan, Watson, & Woodruff, 2011). An example is provided below.

$$TC = \min_x \sum_{t=1}^{T} a_t x_t + \sum_{n \in \mathcal{T}} \pi_n (\sum_{k \in \mathcal{K}_{tn}} b_{nk}^{\top} y_{nk}) \tag{2.4a}$$

subject to

$$\sum_{s=1}^{T} x_s \geq A_{nk} y_{nk} \qquad \forall k \in \mathcal{K}_{tn}, n \in \mathcal{T} \tag{2.4b}$$

$$\sum_{s=1}^{T} x_s \leq u \tag{2.4c}$$

$$B_{nk} y_{nk} = d_{nk} \qquad \forall k \in \mathcal{K}_{tn}, n \in \mathcal{T} \tag{2.4d}$$

$$x_t \in Z_+^I, y_{nk} \in R_+^J, \quad \forall t \in T, k \in \mathcal{K}_{tn}, n \in \mathcal{T}$$

Where x_n represents the investment decisions and y_{nk} the operational sub-problems at node n. Coefficients a_n and b_{nk} are thus related to investment- and operational costs, respectively. Stages are denoted as t and should not be mixed with the operational, hourly time scale. The multistage version would minimize the expected costs at all nodes, for both investments and operation, such as in the following formulation.

$$TC = \min_x \{ \sum_{n \in \mathcal{T}} \pi_n (a_t x_t + \sum_{k \in \mathcal{K}_{tn}} b_{nk}^{\top} y_{nk}) \} \tag{2.5a}$$

subject to

$$\sum_{m \in \mathcal{P}(n)} x_m \geq A_{nk} y_{nk} \qquad \forall k \in \mathcal{K}_{tn}, n \in \mathcal{T} \tag{2.5b}$$

$$\sum_{m \in \mathcal{P}(n)} x_m \leq u \qquad \forall n \in \mathcal{S}_T \tag{2.5c}$$

$$B_{nk} y_{nk} = d_{nk} \qquad \forall k \in \mathcal{K}_{tn}, n \in \mathcal{T} \tag{2.5d}$$

$$x_m \in Z_+^I, y_{nk} \in R_+^J, \quad \forall t \in T, k \in \mathcal{K}_{tn}, n \in \mathcal{T}$$

The notations for the two-stage and multistage models above refers to the scenario tree structure, as briefly mentioned in the section on scenario generation. Recall that the nodes in the tree $n \in \mathcal{T}$ are visited in topological ordering $\sigma(\mathcal{T})$.

The value of incorporating uncertainty

Since stochastic programs relatively complicated to model and solve, quantifying the potential trade-off between deterministic and stochastic programs is of particular importance. Two concepts that could be used to answer this is, (a) the Expected Value of Perfect Information (EVPI), and (b), the Value of the Stochastic Solution (VSS). In the following, a short introduction to those concepts is presented with relevant references being (Birge & Louveaux, 2011) and (Huang & Ahmed, 2009).

A decision maker's best available tool to incorporate as much information as possible is, in our case, a stochastic program. Hence, the maximum cost that a decision maker is willing to pay for perfect information must be equivalent the expected cost savings between the latter and perfect foresight. Thus, the expected value of the deterministic wait-and-see solutions should be subtracted from the more costly stochastic solution, representing the EVPI.

Furthermore, the VSS can be calculated by evaluating outcomes of using the expected value strategy, which represent the expected value of using the expected scenario (EEV). With this, the cost of using the expected value solution in different scenarios is evaluated. The latter is a more costly approach than the stochastic solution, since the first stage decision cannot react to the risk of different scenarios to evolve. The difference between the two objective values is the VSS.

Alternatively, one could search for optimal solutions individually for all scenarios, which is know as the *distribution problem*, i.e. a generalization of sensitivity analysis or parametric analysis in linear programming (Birge & Louveaux, 2011). The expected value of all these solutions is known as the *wait and see* solution:

$$WS = E_{\xi}[\min_{x} Z(x, \xi)] = E_{\xi}[Z(\bar{x}(\xi), \xi)] \tag{2.6}$$

The WS is then compared with the so called *here and now* solution, which corresponds to the recourse problem (RP). In other words, the stochastic solution;

$$RP = \min_{x} \quad E_{\xi} Z(x, \xi) \tag{2.7}$$

with an optimal solution x^*. The EVPI is the difference between the RP and the WS solution:

$$EVPI = RP - WS \tag{2.8}$$

It is not easy to always measure the WS solution due to lack of information, in addition to deriving a set of multiple solutions instead of just one. Hence, it might be more tempting to solve the *expected value problem* or *mean value problem* where all random variables are replaced by their expected values (Maggioni & Wallace, 2012).

$$EV = \min_{x} \quad Z(x, \bar{\xi}) \tag{2.9}$$

where $\bar{\xi} = E(\xi)$ is the expectation of ξ. The VSS measures how good, or how bad, a decision $\bar{x}(\bar{\xi})$ (optimal solution of EV) is in terms of RP. However, by first defining the *expected result of using the EV solution* one could derive the VSS as follows:

$$EEV = E_{\xi}[Z(\bar{x}(\bar{\xi}), \xi)] \tag{2.10}$$

The EEV measures how the expected value solution, $\bar{x}(\bar{\xi})$, performs when allowing the second stage decision to be chosen optimally as functions of $\bar{x}(\bar{\xi})$ and ξ. The VSS is therefore:

$$VSS = EEV - RP \tag{2.11}$$

The VSS is thus the cost of ignoring uncertainty when decisions are being made before information is known.

For any stochastic program, it is shown that the EVPI and the VSS always is greater than, or equal to, zero:

$$\begin{aligned} EVPI &\geq 0 \\ VSS &\geq 0 \end{aligned} \tag{2.12}$$

For stochastic programs with a *fixed recourse matrix* and *fixed objective coefficients*, the following inequalities are true (Birge & Louveaux, 2011):

$$\begin{aligned} EVPI &\leq EEV - EV \\ VSS &\leq EEV - EV \end{aligned} \tag{2.13}$$

2.2.4 Strategic model

Aside from incorporating uncertainty in TEP, another important aspect is strategic behaviour. In some cases, a welfare optimal solutions from those models presented in preceding sections might not always be a realistic ones. This because of conflicting objectives among players that aims to optimize their own benefits, instead of benefits to the system as a whole (welfare optimal). Thus, the following questions could arise:

- What would be the outcome if everyone optimize with respect to their own interests?
- Given the latter, what is the value of cooperation? That is, a fully functioning allocation scheme or energy policy that makes it beneficial for everyone to cooperate?

These are questions that could be answered by comparing the solutions of a cooperative and non-cooperative model. However, care should be taken as non-cooperative models usually represent what we ”want to model” or what we believe is likely to happen. As Paul Krugman once phrased it (when thinking of markets):

> “ ”
>
> Paul Krugman, *All perfect markets are perfect in the same way: all imperfect markets imperfect in their own way.*

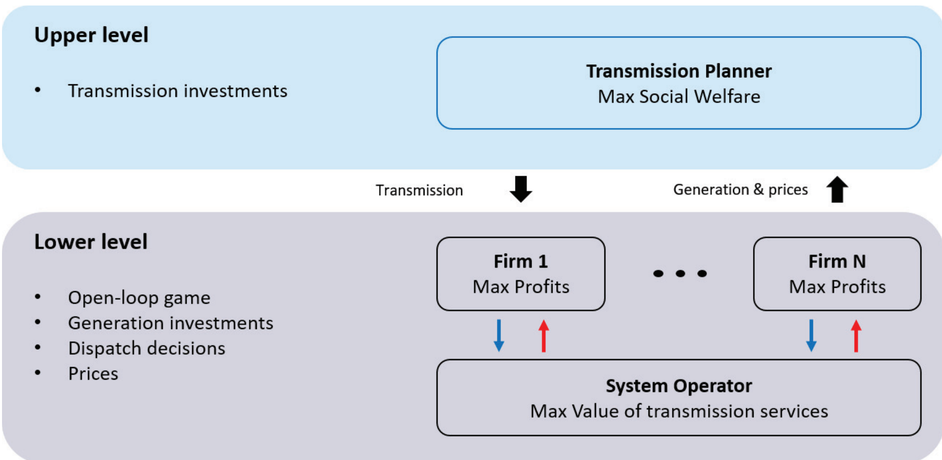


Figure 2.12: Illustration of a bi-level program. In this case a transmission planner that optimize investment decisions while trying to anticipate optimal generation expansion and dispatch. This is known as *proactive* planning and can be recast as a mixed-inter linear program such as the one shown by Equations (2.1). Thanks to Prof. Francisco Muñoz at Universidad Adolf Ibanez for this illustration.

A common approach in solving such problems is to formulate bi- or multi-level programs (Pozo et al., 2017). That is, optimization models that are subject to other optimization models (or optimal solutions). For instance, figure 2.12 illustrates a bi-level program where multiple generation entities maximize profits with generation investments and dispatch subject to prices from the market clearing. This comprise the lower level. In turn, an upper level problem exploits this information to optimize transmission investments. The combination of the two levels is called *proactive planning* where a transmission planner tries to anticipate how generation companies respond. Contrary, a reactive approach would be based on decisions already made without trying to anticipate changes.

Understanding the hierarchical structure of bi- and three-level programs, and its coupling, is useful. In the following, this structure is described more in detail with discussions around relevant solution methods. Again, the expansion planning model is used as an example on how one could migrate from welfare optimization to also consider strategic interaction among agents in the system. In this case, particularly among countries. This is relevant in terms of quantifying the value of cooperation, which also will be put in context in the Post Analytics section.

For a more comprehensive introduction on this matter, in context of expansion planning, please consult with one of the two Master's Theses co-supervised by the author (Bjerketvedt, 2017; Risanger, 2018).

Model structure

For the sake of simplicity, start by considering the most general form of a strategic investment model which is a bi-level program (see Figure 2.12). A bi-level program means that there is an optimization problem (upper level) subject to another optimization problem (lower level). The upper level could be for transmission investment decisions that maximize national welfare, while the lower level problem could be, as the figure suggests, generation companies maximizing their profits.

Since the lower level (LL) problem is linear and continuous, it is also convex. And since it is convex, it can be recast with Karush-Kuhn-Tucker (KKT) conditions for optimality, which is know as necessary and sufficient due to the convexity of the problem in question (Kuhn & Tucker, 1951). Consequently, the model as a whole will now comprise one objective function (UL) subject to UL constraints and KKT conditions from LL. This yields a mathematical problem with equilibrium constraints (MPEC).

Solving MPEC problems can be challenging as their structure often depends on optimality conditions, such as KKT or strong duality, which yields complementarity conditions and bi-linear terms, respectively. The former is non-convex. In turn, these could violate the conditions for being necessary and sufficient when deriving optimality upstream in the hierarchy. A potential algorithm for solving a problem like this could be to visit each possible solution in an iterative manner (multiple Nash Equilibria) and add cuts that avoids this solution being revisited. However, this is a cumbersome approach. Also, other solutions might exist since these would be based on unnecessary KKT conditions.

In relation to the nature of the problem structure investigated in this thesis, a new approach has been carried out together with a master student, exploiting the relationship between binary variables of the linear complementarity conditions and their duals. This allows for a reformulation into a MILP (Risanger, 2018).

Recast a MPEC to a MILP

In contrast to the cooperative model in Equations (2.1), strategic decisions that lead to sub-optimal welfare solutions will now be studied. Since this involves optimization programs subject to other optimization programs, reformulations are needed in order to recast the whole model into one optimization program. The next subsections will go through this procedure in brief, following the three-level structure depicted in Figure 2.13.

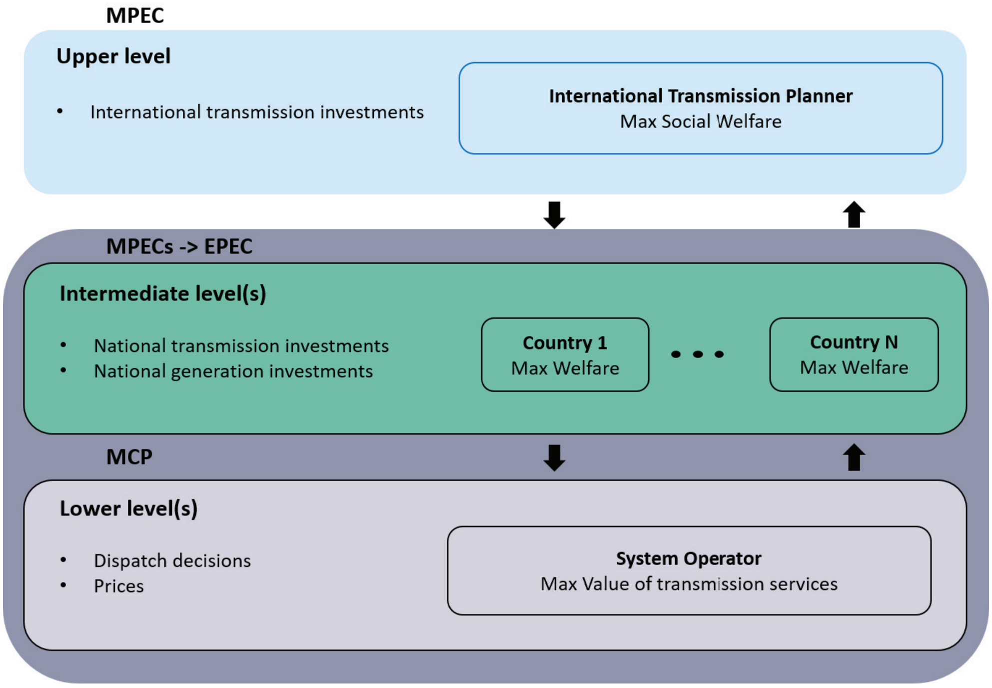


Figure 2.13: Illustration of a three-level program where a supra-national planner (upper level) invests in international infrastructure while anticipating optimal, national response (intermediate level) in terms of domestic transmission- and/or generation investments. All this under perfect competition in lower level.

The bi-linear (non linear) terms in the MPEC could arise in the objective function (e.g. price from LL multiplied with generation levels) and in the complementary conditions (from KKT derivations of LL problem). The complementary conditions are bi-linear since it claims that the product of primal and dual variables has to equal to zero (dependent on whether the respective constraints in the primal problem is binding, or not). These bi-linear terms makes the problem non-convex and very difficult to solve. However, one can linearize these terms and reformulate MPEC problem into a MILP problem (which can be solved with off-the-shelf solvers like Gurobi or Cplex). The alternatives are as follows (see e.g. (Conejo, Baringo Morales, Kazempour, & Siddiqui, 2016)):

1. **Objective function**: Utilize strong duality in LL problem which, together with the KKT- and complementarity conditions, can be used to reformulate the bi-level terms in a linear fashion.
2. **Complementarity conditions**: Use a set of auxiliary variables to replace the variable product constraints (which must hold at zero for strong duality). This requires ”big-M” parameters that has to be tuned by solving the MILP problem and checking if the product of primal and duals are zero.

The MILP can be solved as it is, or one could decompose the problem into sub-problems using e.g. Benders decomposition (Conejo et al., 2016). Recall that there are coupling variables from the UL investment problem in the LL market clearing problems. That is, all hourly market clearings are dependent on the capacity investments in the UL problem. This coupling could be exploited to decompose all LL problems into independent sub-problems (which again can be solved in parallel), and add cuts to the UL "master problem" projecting the utility function, or solution space, that capacity investments yield in market operation.

- **Direct solution**: solve the full MILP. This might be intractable depending on the size of the model.

- **Decomposition**: Utilize coupling variables (capacity investments) to decouple the hourly market clearing. Each market clearing problem yields a linear program (LP) that can produce cuts with capacity investment variables fixed at different levels (according to the Benders decomposition algorithm).

Considering Equations (2.1), the above would apply as follows. The lower level ISO market operation problem is given by minimizaion of total system operational costs in Equations (2.1). That is, minimization of OC subject to Equations (2.19b)-(2.19e), which represents a welfare maximizing ISO clearing the market under the assumption of perfect competition (generation levels are computed endogenously with respect to their marginal costs) and inelastic demand. This linear, continuous and thus convex optimization model yields KKT conditions that are necessary and sufficient. Necessary as it captures all possible equilibria, and sufficient since it could find a global optimum. The KKT conditions are derived from the Lagrangian function of OC subject to Equations (2.19b)-(2.19e):

$$
\begin{aligned}
L = & \sum_{t\in T} \omega_t \Big(\sum_{i\in G} (MC_i + CO2_i) g_{it} + \sum_{n\in N} VOLL s_{nt}\Big) \\
& + \lambda_{nt}\Big[\sum_{i\in G_n} g_{it} + \sum_{b\in B_n^{in}} f_{bt}(1-l_b) - \sum_{b\in B_n^{out}} f_{bt} + s_{nt} - \sum_{l\in L_n} D_{lt}\Big] \\
& + \bar{\rho}_{it}[g_{it} - \gamma_{it}(P_i^e + x_i)] \\
& - \underline{\rho}_{it}[g_{it} - P_i^{min}] \\
& + \epsilon_i\Big[\sum_{t\in T} \omega_t g_{it} - E_i\Big] \\
& + \bar{\alpha}_{bt}[f_{bt} - (P_b^e + y_b^{cap})] \\
& - \underline{\alpha}_{bt}[f_{bt} + (P_b^e + y_b^{cap})] \\
& - \phi_{nt}[s_{nt}]
\end{aligned}
\tag{2.14a}
$$

Equation (2.15) shows the resulting Lagrangian function which comprise the OC plus the dual variables in the primal problem, multiplied with the primal constraints when they sum to less than, or equal to, zero. The KKT conditions can be found by differentiating the Lagrangian function with respect to all primal variables, plus any equality constraints from the primal problem, plus complementarity conditions for all the inequality constraints in the primal problem, plus the boundaries for dual variables for primal equality constraints (Conejo et al., 2016).

The following equations contains the KKT conditions for first-order optimality:

Differentials of Lagrangian:

$$\omega_t(MC_i + CO2_i) + \lambda_{n(i)t} + \bar{\rho}_{it} - \underline{\rho}_{it} + \epsilon_i\omega_t = 0 \qquad \forall i,t \in G,T \tag{2.15a}$$

$$\omega_t VOLL + \lambda_{nt} - \phi_{nt} = 0 \qquad \forall n,t \in N,T \tag{2.15b}$$

$$\lambda_{n(b^{in})t}(1-l_b) - \lambda_{n(b^{out})t} + \bar{\alpha}_{bt} - \underline{\alpha}_{bt} = 0 \qquad \forall b,t \in B,T \tag{2.15c}$$

Primal equality constraints:

$$\sum_{i\in G_n} g_{it} + \sum_{b\in B_n^{in}} f_{bt}(1-l_b) - \sum_{b\in B_n^{out}} f_{bt} + s_{nt} - \sum_{l\in L_n} D_{lt} = 0 \qquad \forall n,t \in N,T \tag{2.15d}$$

Complementarity conditions for primal inequality constraints:

$$0 \le (g_{it} - \gamma_{it}(P_i^e + x_i)) \perp \bar{\rho}_{it} \ge 0 \qquad \forall i,t \in G,T \tag{2.15e}$$

$$0 \le g_{it} \perp \underline{\rho}_{it} \ge 0 \qquad \forall i,t \in G,T \tag{2.15f}$$

$$0 \le (\sum_{t\in T} \omega_t g_{it} - E_i) \perp \phi_i \ge 0 \qquad \forall i \in G \tag{2.15g}$$

$$0 \le (f_{bt} - (P_b^e + y_b^{cap})) \perp \bar{\alpha}_{bt} \ge 0 \qquad \forall b,t \in B,T \tag{2.15h}$$

$$0 \le (f_{bt} + (P_b^e + y_b^{cap})) \perp \underline{\alpha}_{bt} \ge 0 \qquad \forall b,t \in B,T \tag{2.15i}$$

$$0 \le (s_{nt}) \perp \phi_{nt} \ge 0 \qquad \forall n,t \in N,T \tag{2.15j}$$

Dual variables from equality constraints are free:

$$\lambda_{nt} \in \text{free} \qquad \forall n,t \in N,T \tag{2.15k}$$

Those KKT conditions represents optimal market operation, which can be added into any upper level problems such as investment decisions. Note that investment decisions from the upper levels appear as parameters in the lower level problem. However, recall that the KKT conditions comprise the caveat of bi-linear expressions for the complementarity constraints. One could use aforementioned linearization techniques to cope with this, but one would have to choose wisely depending on the nature of the upper level problems. Here are some alternatives:

1. Replace complementarity constraints with disjunctive constraints by representing auxiliary variables (i.e. "extra" variables) (Fortuny-Amat & McCarl, 1981) and appropriately selected big-M's for primal- and dual variables. The latter can be checked by solving the resulting MILP program. However, this means that differentiations of the national-planner problem (second, or intermediate, level) can be with respect to binary variables, which will lead to non-exact solutions.

2. Replace complementarity constraints using Schur's decomposition and SOS1-type variables (Siddiqui & Gabriel, 2013). This method would also require binary variables.

3. Use strong duality (Ruiz, Conejo, & Smeers, 2012) to represent the optimization program by a set of constraints (primal objective equals dual objective). This method does not require binary variables. Moreover, it can be used as an exact linearization of upper level objective functions which often comprise price times quantity.

The most convenient of the linearization methods asserted above is the strong duality approach, which leaves out the need for binary variables. This means that one could represent the lower level problem as an integral part of more than one upper level problem (i.e. one could derive new KKT's differentiating over continuous variables, only). The reformulated version of Equations (2.1) would then look like:

Differentials of Lagrangian:

$$\omega_t(MC_i + CO2_i) + \lambda_{n(i)t} + \bar{\rho}_{it} - \underline{\rho}_{it} + \epsilon_i \omega_t = 0 \qquad \forall i, t \in G, T \qquad (2.16a)$$

$$\omega_t VOLL + \lambda_{nt} - \phi_{nt} = 0 \qquad \forall n, t \in N, T \qquad (2.16b)$$

$$\lambda_{n(b^{in})t}(1 - l_b) - \lambda_{n(b^{out})t} + \bar{\alpha}_{bt} - \underline{\alpha}_{bt} = 0 \qquad \forall b, t \in B, T \qquad (2.16c)$$

Primal equality constraints:

$$\sum_{i \in G_n} g_{it} + \sum_{b \in B_n^{in}} f_{bt}(1 - l_b) - \sum_{b \in B_n^{out}} f_{bt} + s_{nt} - \sum_{l \in L_n} D_{lt} = 0 \qquad \forall n, t \in N, T \qquad (2.16d)$$

Strong duality instead of complementarity conditions:

$$\begin{aligned}
&\sum_{t \in T} \omega_t (\sum_{i \in G} (MC_i + CO2_i) g_{it} + \sum_{n \in N} VOLL s_{nt}) \leq \sum_{t \in T} \sum_{n \in N} D_{l(n),t} \lambda_{nt} \\
&+ \sum_{t \in T} \sum_{i \in G} \gamma_{it} (P_i^e + x_i) \bar{\rho}_{it} - \sum_{t \in T} \sum_{i \in G} P_i^{min} \underline{\rho}_{it} + \sum_{t \in T} \sum_{b \in B} (P_b^e + y_b^{cap}) \bar{\alpha}_{bt} \qquad (2.16e) \\
&+ \sum_{t \in T} \sum_{b \in B} (P_b^e + y_b^{cap}) \bar{\alpha}_{bt} + \sum_{t \in T} \sum_{b \in B} (P_b^e + y_b^{cap}) \underline{\alpha}_{bt} + \sum_{i \in G} E_i \epsilon_i
\end{aligned}$$

Dual variables from equality constraints are free:

$$\lambda_{nt} \in \text{free} \qquad \forall n, t \in N, T \qquad (2.16f)$$

The second level problem represent individual countries maximizing national welfare. That is, they maximize national welfare anticipating the outcome in the lower level (prices). Each national problem will therefore be to maximize national welfare subject to the third level problem given in Equations (2.16), yielding a MPEC for each country and an EPEC when considering a Nash-Cournot game between all national planners (countries). The resulting MPEC would play out as shown in Equations (2.17):

$$\min_{x,g,f,s,\lambda,\bar{\rho},\underline{\rho},\epsilon,\bar{\alpha},\underline{\alpha},\phi} \quad -[a\cdot(PS_c+CS_c+CR_c)-\sum_{i\in G_c} CX_i x_i] \tag{2.17a}$$

where

$$PS_c=\sum_{t\in T}\omega_t\sum_{i\in G_c}(\lambda_{n(i)t}-MC_i-CO2_i)g_{it} \tag{2.17b}$$

$$CS_c=\sum_{t\in T}\omega_t\sum_{n\in N_c}(VOLL-\lambda_{nt})D_{nt} \tag{2.17c}$$

$$CR_c=0.5\sum_{t\in T}\omega_t(\sum_{b\in B_c^{in}}(\lambda_{n^{from}(b)}-\lambda_{n^{to}(b)})f_{bt}+\sum_{b\in B_c^{out}}(\lambda_{n^{to}(b)}-\lambda_{n^{from}(b)})f_{bt}) \tag{2.17d}$$

Primal lower level constraints:

$$\sum_{i\in G_n} g_{it}+\sum_{b\in B_n^{in}} f_{bt}(1-l_b)-\sum_{b\in B_n^{out}} f_{bt}+s_{nt}=\sum_{l\in L_n} D_{lt} \qquad \forall n,t\in N,T \tag{2.17e}$$

$$P_i^{min}\le g_{it}\le\gamma_{it}(P_i^e+x_i) \qquad \forall i,t\in G,T \tag{2.17f}$$

$$\sum_{t\in T}\omega_t g_{it}\le E_i \qquad \forall i\in G \tag{2.17g}$$

$$-(P_b^e+y_b^{cap})\le f_{bt}\le(P_b^e+y_b^{cap}) \qquad \forall b,t\in B,T \tag{2.17h}$$

Optimality conditions for lower level:

$$\omega_t(MC_i+CO2_i)+\lambda_{n(i)t}+\bar{\rho}_{it}-\underline{\rho}_{it}+\epsilon_i\omega_t=0 \qquad \forall i,t\in G,T \tag{2.17i}$$

$$\omega_t VOLL+\lambda_{nt}-\phi_{nt}=0 \qquad \forall n,t\in N,T \tag{2.17j}$$

$$\lambda_{n(b^{in})t}(1-l_b)-\lambda_{n(b^{out})t}+\bar{\alpha}_{bt}-\underline{\alpha}_{bt}=0 \qquad \forall b,t\in B,T \tag{2.17k}$$

Strong duality in lower level:

$$\begin{aligned}&\sum_{t\in T}\omega_t(\sum_{i\in G}(MC_i+CO2_i)g_{it}+\sum_{n\in N}VOLLs_{nt})\le\sum_{t\in T}\sum_{n\in N}D_{l(n),t}\lambda_{nt}\\&+\sum_{t\in T}\sum_{i\in G}\gamma_{it}(P_i^e+x_i)\bar{\rho}_{it}-\sum_{t\in T}\sum_{i\in G}P_i^{min}\underline{\rho}_{it}+\sum_{t\in T}\sum_{b\in B}(P_b^e+y_b^{cap})\bar{\alpha}_{bt}\\&+\sum_{t\in T}\sum_{b\in B}(P_b^e+y_b^{cap})\bar{\alpha}_{bt}+\sum_{t\in T}\sum_{b\in B}(P_b^e+y_b^{cap})\underline{\alpha}_{bt}+\sum_{i\in G}E_i\epsilon_i\end{aligned} \tag{2.17l}$$

Dual variables from equality constraints are free:

$$\lambda_{nt}\in\text{free} \qquad \forall n,t\in N,T \tag{2.17m}$$

2.2.5 Computational challenges

Generation and Transmission Expansion Planning (GTEP) models like PowerGIM tends to become large and intractable when accounting for more operational- (timesteps), spatial- (areas), strategic- (multi-level), and/or stochastic details (multi-stage / scenarios). All aforementioned characteristics yield problem structures that potentially can be exploited with different decomposition schemes. Among others, particularly two that have been investigated in relation to the work presented here, namely; Bender's Decomposition (for coupling variables) and Progressive Hedging Algorithm (for coupling constraints).

Decomposition methods are useful when encountering an intractable model, i.e. if it becomes too large to be solved in its extensive form, or when information is to be kept isolated among agents involved in the problem. The name itself is explanatory in the sense that a model is to be decomposed into multiple models that are solved individually.

Models have a decomposable structure if they contain (i) coupling variables and/or (ii) coupling constraints. Sometimes these are also referred to as "complicating" instead of coupling (Conejo et al., 2016), meaning that the extensive form problem collapses into a decomposable structure if the complicating variable or constraint is removed. These structures can be exploited in order to make models tractable, isolate information sharing, or solve them faster.

- **Coupling variables** are variables that can be fixed and still couple blocks/parts of the original incident matrices. That is, "variables occurring frequently in constraints" (right part of Figure 2.14). If the variable is fixed, the model is left with a set of constraints that can be solved individually (sub-problems).

- **Coupling constraints** are constraints that can be relaxed and approximated into the objective function by using dual variables. That is, "constraints that couples most variables" (left part of Figure 2.14). If these are removed, the model is left with a set of constraints that can be solved individually (sub-problems).

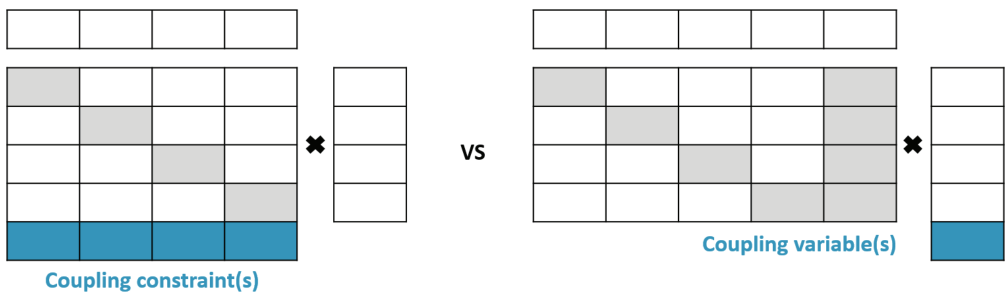


Figure 2.14: Coupling constraints are those that contains all variables in a problem. Similarly, coupling variables are those that are present in all constraints. In some cases, these are referred to as "complicating" since if removed, then the problem collapses into a decomposable structure. Thanks to Prof. Jalal Kazempour at DTU for illustration (with own modifications).

Solving models with coupling constraints

Optimization problems with coupling constraints can be solved with:

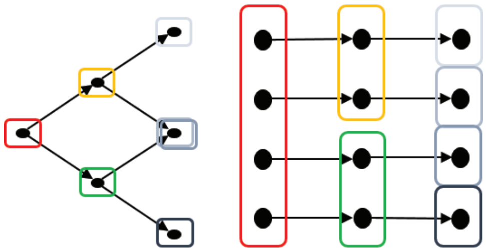


Figure 2.15: Illustration of the progressive hedging algorithm (decomposition of coupling constraints). It can be though of as a scenario tree that is unfolded into an equivalent decision-sequence for all scenarios. In turn, one penalize decisions to be equal to its corresponding nodes in the original scenario tree (indicated by the colored boxes). For instance, in the first node all decisions need to be penalized such that they converge to the same value (red box).

- **Lagrangian Relaxation (LR)**: A good fit for problems with quadratic objective functions and continuous variables. Might not converge with linear objective functions.
- **Augmented Lagrangian Relaxation (ALR)**: Can handle linear objective functions due to quadratic penalty terms. Uses algorithms such as Auxiliary Problem Principle (APP) and Alternating Direction Method of Multipliers (ADMM).
- **Dantzig-Wolfe Decomposition (DWD)**: Exploit block-diagonal structures. Suitable even if sub-problems contains integer variables (relative to Benders).

More information about these can be found in e.g. (Conejo et al., 2016) and (Birge & Louveaux, 2011). The relaxation of constraints with dual variables in the objective function is handled by iteratively fixing and updating them. The dual variables are updated with e.g. (i) sub-gradient method, (ii) cutting plane method, (iii) bundle method, and (iv) trust region method. The main difference between LR and ALR is the additional penalty term in the sub-problems, where e.g. ADMM is used to cope with the quadratic term.

One of the algorithms used during the course of this PhD project is the progressive hedging algorithm (PHA) (see Figure 2.15). The PHA is based on scenario-wise decomposition and it is very similar to the Lagrangian relaxation, in terms of relaxing the non-anticipative constraints (”unfolding” the scenario three structure in Figure 2.15) and adding penalty terms to the objective function. Nodes in the decomposed scenario tree that are supposed to represent their original node in the scenario tree, such as the ones marked with colored boxes in Figure 2.15, are penalized in the objective function until they converge to the same decision values. Intuitively speaking, one would have to make the same decision in nodes where the same information about the future is known.

Solving models with coupling variables

The key idea with solution algorithms coping with coupling variables is that one would like to approximate a cost-to-go function with respect to coupling variable(s). This is done by solving sub-problems and collecting sensitivity information that could be used to reflect costs in the master problem.

Again, the structure would typically take a hierarchical form in the same way as the bi-level model presented in previous section. For instance, a decomposable structure for PowerGIM

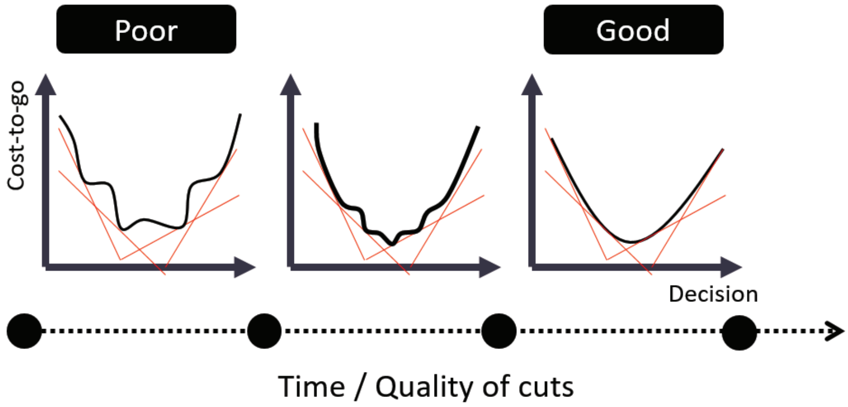


Figure 2.16: Illustration of linearized cuts (red lines) that represent the cost-to-go function using e.g. Benders (decomposition of coupling variables). Here in a sequential fashion over time in order to show the potential impact of integer variables. This because cuts are derived from a linearized representation of the model in the backward iterations (when collecting information about future costs, i.e. cost-to-go).

would be something like this (equivalent to Figure 2.12):

- **Master (upper level) problem**: Minimize investment costs for grid and generator expansion. Constraining the solution space with "cuts" that describe the "cost-to-go" for subsequent sub-problems.
- **Sub-problems (lover level)**: Minimize operational costs for electricity dispatch. Assuming fixed investment variables from the upper-level solution in the same iteration.

Some well known algorithms include:

- **Dynamic Programming (DP)**: Discretize coupling variable into a set of trails, solve all sub-problems with all trail values. The drawback is that it explodes in size. For instance, 10 variables and five discretizations yields 5^{10} discrete values.
- **Dual Dynamic Programming (DDP)**: Approximate cost-to-go function with analytical sensitivity functions, rather than discretized values (as with DP), using dual variables from the sub-problems. The main drawback here is that the sub-problems should be linear.
- **Benders' Decomposition (BD)**: A version of DDP with a systematic iterative approach in constructing cuts from dual values in the sub-problems. If the original objective function is convex with respect to coupling variables, global optimum is guaranteed. For two-stage stochastic problems this approach is called *L-shaped decomposition*.
- **Nested Benders' Decomposition**: Using BD for multistage problems, i.e. solving from first- to last stage in order to collect duals (forward iteration) and add these into the nested master problems (backward iteration).
- **Stochastic Dual Dynamic Decomposition (SDDP)**: Nested BD for stochastic multistage problems. Other versions include SDDiP with the caveat of containing integers, making the standard forward-backward algorithms less accurate due to the need of linearizing

integer variables. This impact on cuts is illustrated from right to left in Figure 2.16. For the latter case, *strengthened Benders* (Zou, Ahmed, & Sun, 2017) would be as tight, or tighter, than normal Benders' cuts.

In general, integer and binary variables might complicate the utilization of dual variables (sensitivities). However, one could still generate cuts based on primal values. Primal BD, i.e. the cutting-plane method, could be an alternative (Birge & Louveaux, 2011).

Example with coupling variables in PowerGIM

Instead of only considering the extensive form, an example is here carried out on how one could exploit the decomposable structure of PowerGIM. To this end, utilize coupling variables (capacity investments) to decouple the hourly market clearing. Each market clearing problem would in turn result in a linear program (LP) where cuts can be derived from its dual variables. This is possible by first assuming capacity investment variables, then iteratively adjusting those with respect to the impact of adding cuts to the solution space (which complies with the BD algorithm).

The master problem could, e.g. , be only to consider investments as shown in Equations (2.18):

$$\min_{x,y,z} \sum_{b\in B}(C_b^{fix} y_b^{num} + C_b^{var} y_b^{cap}) + \sum_{n\in N} CZ_n z_n + \sum_{i\in G} CX_i x_i + a \cdot \alpha(x,y) \tag{2.18a}$$

where

$$\alpha = \min_{g,f,s} \sum_{t\in T} \omega_t (\sum_{i\in G}(MC_i + CO2_i) g_{it} + \sum_{n\in N} VOLLs_{nt}) \tag{2.18b}$$

$$C_b^{fix} = B + B^d D_b + 2CS_b \qquad \forall b \in B \tag{2.18c}$$

$$C_b^{var} = B^{dp} D_b + 2CS_b^p \qquad \forall b \in B \tag{2.18d}$$

subject to

$$y_b^{cap} \leq P_b^{n,max} y_b^{num} \qquad \forall b \in B \tag{2.18e}$$

$$\sum_{b\in B_n} y_b^{num} \leq M z_n \qquad \forall n \in N \tag{2.18f}$$

$$\alpha \geq \pi_t (b_t - E_t(x,y)) \qquad \forall t \in T \tag{2.18g}$$

$$x_i, y_b^{cap} \in R^+, \quad y_b^{num} \in Z^+, \quad z_n \in \{0,1\}$$

Consequently, the remainder would need to include market operation for each time step as shown in Equations (2.19).

$$\min_{g,f,s} \sum_{t\in T} \omega_t (\sum_{i\in G}(MC_i + CO2_i) g_{it} + \sum_{n\in N} VOLLs_{nt}) \tag{2.19a}$$

subject to

$$\sum_{i\in G_n} g_{it} + \sum_{b\in B_n^{in}} f_{bt}(1-l_b) - \sum_{b\in B_n^{out}} f_{bt} + s_{nt} = \sum_{l\in L_n} D_{lt} \qquad (\lambda_{nt}) \quad \forall n,t \in N,T \tag{2.19b}$$

$$P_i^{min} \leq g_{it} \leq \gamma_{it}(P_i^e + x_i) \qquad (\bar{\rho}_{it}, \underline{\rho}_{it}) \quad \forall i,t \in G,T \tag{2.19c}$$

$$\sum_{t\in T} \omega_t g_{it} \leq E_i \qquad (\epsilon_i) \quad \forall i \in G \tag{2.19d}$$

$$-(P_b^e + y_b^{cap}) \leq f_{bt} \leq (P_b^e + y_b^{cap}) \qquad (\bar{\alpha}_{bt}, \underline{\alpha}_{bt}) \quad \forall b,t \in B,T \tag{2.19e}$$

$$x_i, y_b^{cap}, g_{it}, s_{nt} \in R^+, \quad f_{bt} \in R, \quad y_b^{num} \in Z^+, \quad z_n \in \{0,1\}$$

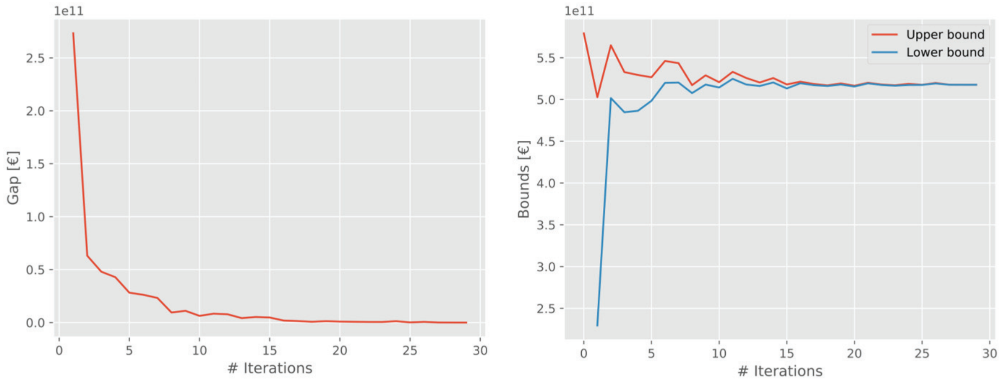


Figure 2.17: Benders' decomposition algorithm applied to PowerGIM. Here, the master problem encompass investments, while the sub-problems represent one operational hour, each.

The cuts are derived based on the sub-problems dual functions, utilizing strong duality, as demonstrated by Equation (2.20).

$$\alpha = \min_{g,f,s} = \max_{\lambda,\rho,\epsilon,\alpha} \sum_{n,t\in N,T} (\sum_{l\in L_n} D_{lt})\lambda_{nt} + \sum_{i,t\in G,T} \gamma_{it}(P_i^e + x_i)\bar{\rho}_{it} + \sum_{i\in G} E_i\epsilon_i + \sum_{b,t\in B,T} (P_b^e + y_b^{cap})\bar{\alpha}_{bt} \tag{2.20a}$$

These aggregate cuts are then added into the master problem in an iterative fashion, as summarized in Algorithm 1. Figure 2.17 illustrates the achieved convergence when applying BD to PowerGIM, where the left hand plot shows the difference between upper- and lower bound (which are shown in the right hand plot).

Algorithm 1 Benders' Decomposition

1: **Initialize**: Set $i = 1$, $LB = -\infty$ and fix master variables ▷ $i = 1$
2: Solve all sub-problems: Collect dual values and UB
3: **Convergence?** If $|UB - LB| \leq \epsilon$ break. Otherwise, continue. ▷ $i \leftarrow i + 1$
4: **Solve master**: Add cut $\alpha^{(i)}$ from sub-problems as new LB, get new master variables and go to step 2.

2.3 Post analytics

Given a model and the possibility to analyze different interdependencies and scenarios, there are many ways to interpret and analyze this. The remainder will focus on the most relevant post analytics, aside from standard visualization and analyses. First, useful methods from cooperative game theory are discussed in context of assessing bargaining power and incentives for cooperation. This is partly also related to the cooperative and non-cooperative models presented in previous section. Cooperative game theory could be used to bridge the gap between the two. Second, selected methods from systems engineering are used to broaden the context of what concerns expansion planning and hopefully provide more insights that are both (i) problem specific, and (ii) supporting to the understanding of operations research and game theory. Particularly for the interpretation of solutions; whether a solution is robust with respect to uncertainty and risk, or if there are evident patterns that might describe bargaining power.

2.3.1 The cost-benefit allocation problem

Finding a set of optimal investments is important. However, making sure that these materialize is also of great importance. That is, designing appropriate energy policy, allocation schemes or some form of compensation in cases where incentives are weak or non-existent for a given investment portfolio. Hence, the cost-benefit allocation problem is equally important, if not more, than the decision support models used to find optimal and robust investment portfolios (whether it is infrastructure or generation, or both). The benefits of cooperation in reaching future energy- and climate targets are significant, in particular when leveraging geographical diversification in a multinational context (Strbac et al., 2014; NSCOGI, 2014; ENTSO-E, 2016).

International transmission investments are capital intensive and bulky, in addition to being exposed to environmental- and political tension due to its impact on both land usage and material price impacts in adjacent regions, or countries (W. W. Hogan, 2018). In cases where one region benefits more than the other, it is quintessential to understand why and how to make such scenarios fair and consequently likely to develop. Even surrounding areas might be relevant to consider, as these can free-ride or be negatively affected by the projects in question (through externalities) (Kristiansen et al., 2018).

The latter is relevant for what the EU Commission defines as Projects of Common Interest (PCI), that is projects for the greater good in terms of system (multinational) benefits. Such projects deliver benefits to at least two European member states, in addition to further supporting market integration, enhancing security of supply, and contribute to reducing environmental impact. However, even though two countries benefit, the question is who gets what, and how much. The funding provided through Connecting Europe Facility (CEF) may not provide sufficient budgets to compensate for uneven and unfair welfare impacts that arise after necessary upgrades are made in the power system. In combination with the ambitious energy- and environmental targets in Europe it is crucial to have a proper allocation mechanism in place, which could help speed up and facilitate for cooperative, international investments.

Traditional allocation schemes

Traditionally, suggested methods for allocation of costs and benefits associated with international transmission investments comprise simple rules such as (i) the Equal Sharing Principle (ESP), or (ii), the Positive Net Benefit Differential (PNBD). The former divides costs equally among the participating countries, while the latter splits costs in proportion to estimated benefits (i.e. according to the beneficiaries pay principle). Among the two, the PNBD is shown to be appropriate since it internalizes negative externalities (Konstantelos et al., 2017), i.e. the impact on surrounding countries (Bushnell & Stoft, 1996, 1997). Assuming three projects, A, B, and C, there are at least three aspects that both ESP and PNBD cannot account for, and that is:

- Incremental value from a country.
- Bargaining power.
- Deployment sequence.

First, by neglecting the economic value that results from a country's support for one or a group of projects (e.g. , welfare changes for all countries if one nation decides not to support a project), detrimental projects could arise since incentives are not strong enough for system optimal designs (W. W. Hogan, 1999b; Hans Nylund, 2009). For instance, countries with abundant flexible generation, such as hydro in Norway, may be responsible for a large fraction of the cost savings that result from an integrated NSOG network. Secondly, strategic incentives are ignored, meaning that one should consider that each country might see stronger incentives in forming smaller subcoalitions — where they collaterally could achieve higher payoffs, but at the expense of inefficient system designs. Finally, the deployment sequence of transmission projects does affect the value of other projects in the same network (Banez-Chicharro, Olmos, Ramos, & Latorre, 2017b) (e.g. , incremental value of a project for the system if it is considered first or last in a sequence of installations). Any of these features could weaken the incentives for countries to join the grand coalition and lead to failure to implement a socially-optimal set of international transmission interconnections (Hans Nylund, 2009).

There are other allocation methods that incorporate the impact of deployment sequence, such as Take Out One at a Time (TOOT) and Put In one at a Time (PINT), but these do not value the marginal contribution of all possible sequences of individual projects.

The Shapley Value

An alternative allocation mechanism is the Shapley Value (SV) from cooperative game theory (Lloyd S. Shapley, 1953). Cooperative game theory is an important subject given its limited attention in academia, compared to non-cooperative games (Maskin, 2016). It differs from non-cooperative games in the sense that it is not dependent on a set of strategies, but only a payoff that depends on a characteristic function. Given a characteristic function, there could exist many sets of non-cooperative strategies. By only changing one strategy option along these arrays of strategies, one could potentially distort the whole solution. Thus, cooperative games are more robust in terms of 'predicting' an outcome, independent on the path of strategies. However, in order for it to work, one have to be sure that the grand coalition is formed – that is, assuming that everyone cooperate under absence of externalities. Externalities meaning that coalitions are affected by what other coalitions does. These are indeed strong assumptions, but in many cases it could as well be realistic.

Famous examples that applies the SV include the airport game (Littlechild & Owen, 1973), where the goal is to derive a fair allocation of airport maintenance costs, taking into account that airplanes that cause the most wear and tear (typically larger airplanes) would need to pay more relative to those that cause less maintenance needs (smaller airplanes). Also, the Bankruptcy Game (O'Neill, 1982) in finding a fair allocation of remaining assets to creditors. A more recent and relevant example is one by (Murphy & Rosenthal, 2006) that studies the added value of different energy policies, where the SV unveil a useful summary number for each policy impact without the hidden bias of predefined deployment sequences.

A cooperative game of $|N|$ players has $2^{|N|}$ possible coalitions, and each player can be participate in $2^{|N|} - 2^{(|N|-1)}$ coalitions. In all cases, the SV is calculated as the average marginal value for all possible sequences of player arrival/contribution (airplanes, creditors or energy policies). These marginal values are given by a characteristic function, $v(S)$. In context of infrastructure investments in the NSOG, $v(S)$ is defined as the difference in net benefits (i.e. , sum of producer surplus, consumer surplus, and congestion rents) that result from solving the planning problem under the support of coalition S and a Base Case, where no transmission projects are developed, $v(\emptyset) = 0$. To this end, one could assume that under coalition S, the only transmission interconnections that can be developed are those that are directly connected to host countries that have the power to veto the construction of any lines.

For instance, when computing $v(S)$, an interconnection that goes from country A to country B is considered a candidate investment alternative only if $A \in S$ and $B \in S$. If these two countries do not reach a cooperative agreement, then no transmission interconnections can be built. In this case, the value function is $v(\emptyset) = 0$. On the other hand, if N is the set that represents the grand coalition (i.e. , when all countries reach a cooperative agreement), then $v(N)$ is equal to the total net benefits that would result when considering all transmission interconnections as investment alternatives. Under perfect competition, $v(N)$ is also equal to the welfare gains, or net benefits, that result from these transmission projects. Following the spirit of Regulation (EU) No 347/2013 (EUL, 2013), third-party countries will be included in the negotiations. However, for a different application these could be excluded from the computation of the SV by only considering net benefits for host countries in the value function.

$$\phi_i(N,v) = \frac{1}{|N|!} \sum_{S \subseteq N \setminus \{i\}} |S|!(|N| - |S| - 1)![v(S \cup i) - v(S)] \tag{2.21}$$

The SV payoff to country i is provided by Equation (2.21). This payoff is computed considering all the different ways country i can add value to different coalitions S, which are subsets of the grand coalition N. It captures the marginal contributions from country i, $[v(S \cup i) - v(S)]$, weighted by the $|S|!$ different ways the coalition S could have been formed prior to country i joining it and by the $(|N| - |S| - 1)!$ ways the remaining countries could join the same coalition, summed over all combinations of subsets excluding i ($S \subseteq N \setminus \{i\}$) and averaged by it dividing by $|N|!$, where $|N|!$ is the number of possible orderings of all countries. The resulting payoff vector to each country i, in this case allocation of net benefits, is given by $\phi_i(N,v)$. The n-tuple $(\phi_1(N,v), \phi_2(N,v), ..., \phi_n(N,v))$ is the final allocation of net benefits for all countries under the SV if $n = |N|$.

This means that, by construction, the SV takes into account the average incremental contribution of each country towards the grand coalition, considering all possible development sequences. The result is a fair allocation of net benefits, ignoring strategic incentives for parties to deviate from the grand coalition. In fact, the SV is the only allocation that satisfies an axiomatic definition of fairness (Myerson, 1977):

- Efficiency; that all benefits are distributed among participating countries.

- Symmetry; that countries with the same average incremental contribution receive the same allocation of net benefits.

- Zero player; that countries that do not have veto power get zero net benefits (Narahari, 2014).

Moreover, under certain conditions, the resulting allocation can also be stable — meaning that involved parties lack incentives to deviate from the grand coalition. If stable, then the game is said to be in the core as illustrated with Figure 2.18.

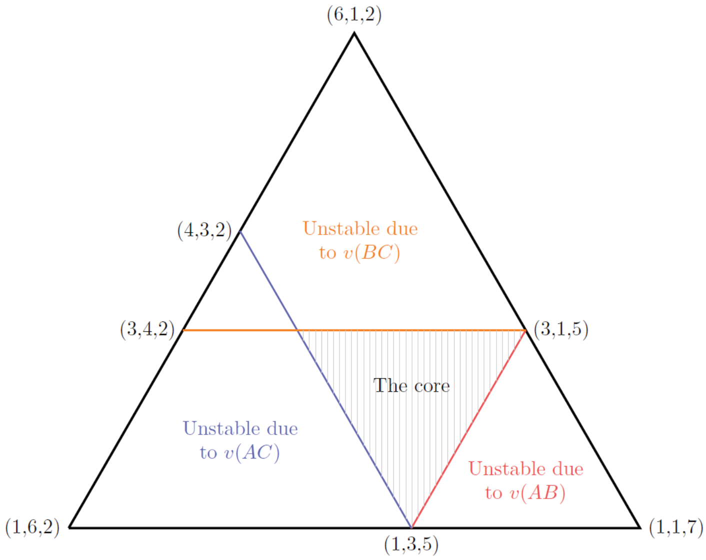


Figure 2.18: Illustration of the core for a three-player game in barycentric coordinates. If the payoff to all players is in the core, then the game is stable. Otherwise, it is not stable since e.g. the characteristic function for subcoalition $v(BC)$ (orange) implies a greater payoff to player B and C, compared to what they receive in the cooperative solution (grand coalition). Thanks to Simon Risanger for illustration (Risanger, 2018).

It has been demonstrated that if a cooperative game is convex, then the SV is in the core (Narahari, 2014). A game is convex if the incentives to join a coalition are weakly increasing on the size of the coalition (Schweizer, 1989). Inequality 2.22 shows the property of convexity for a cooperative game, where the incremental value for country i to join coalition T is higher than, or equal to, the incremental value of joining coalition S, where coalition S is formed by a subgroup of the countries that form coalition T (i.e. , $S \subseteq T$).

$$v(S \cup \{i\}) - v(S) \leq v(T \cup \{i\}) - v(T) \qquad \forall S \subseteq T \subseteq N \backslash \{i\}, \forall i \in N \tag{2.22}$$

Instead of checking for convexity, one could evaluate if a solution is in the core by assessing *group rationality*, as shown in Equation (2.23), by following Algorithm Algorithm 2. The core is denoted $C(N, v)$.

$$C(N, v) = \left\{ \boldsymbol{x} \in X \mid \sum_{i \in S} x_i \geq v(S) \text{ for all } S \subset N \right\} \tag{2.23}$$

Algorithm 2 Check for solutions in the core - group rationality

1: **for all** $S \subset N$ **do**
2: **if** $\sum_{i \in S} x_i < v(S)$ **then**
3: **return** Allocation is *not* in the core
4: **end if**
5: **end for**
6: **return** Allocation is in the core

Aumann-Shapley

An extension of the SV, know as Aumann-Shapley (AS), has been applied in TEP with the purpose of capturing incremental contributions from different players (Banez-Chicharro et al., 2017b, 2017a). That is, the contribution of transmission expansion at all capacity levels from zero to its thought capacity, in contrast to only evaluating the contribution at its thought capacity level (which is the case for SV). However, it is not clear if this is necessary for transmission investments as these are undertaken in bulk capacity levels, anyway.

For instance, PowerGIM will expand bulky capacities, say, at 1000 MW at a time. This is where AS differs from SV, whereas the former calculates the marginal contributions by uniformly increasing the size of investment variables from zero to its thought/optimal value. This means that other investment options are included before a particular one reaches its optimal value, say 1000 MW. However, since PowerGIM contains integer variables, sensitivity information from its capacity constraints (dual variables) cannot be exploited. The latter is quintessential for the AS method. The alternative is, of course, to relax all integer variables in order to achieve a LP.

The fact that AS uses sensitivities has also proven to be easily scalable to larger problems (Junqueira et al., 2007). Although computational issues were not encountered in this thesis, these are the properties of AS that might be beneficial for similar studies.

The Nucleolus

While the SV finds an allocation that satisfies an axiomatic definition of fairness, the nucleolus incorporate the bargaining process to find the most stable solution (Schmeidler, 1969). In its most simple form, this means that the objective is to minimize the dissatisfaction of the least satisfied set of players (subcoalitions S), compared to what is obtained in the grand coalition. A brief summary of the method and its algorithm is provided here, but for interested readers it is recommended to consult with (Risanger et al., 2018) or (Risanger, Kristiansen, & Munoz, 2018).

With this in mind, the reference point for finding such allocations would be the core. The key philosophy with the nucleolus is to find solutions that are as close to the center of the core as possible. However, some slack is given for cases where the core might be empty. For this purpose, an excess function, $e(\boldsymbol{x}, S)$, is defined as follows (see Equation (2.24)).

$$e(\boldsymbol{x}, S) = v(S) - \sum_{i \in S} x_i = v(S) - \boldsymbol{x}(S) \tag{2.24}$$

Where $e(\boldsymbol{x}, S)$ is the difference between the current allocation and the value of forming a subcoalition, S. In turn, the surplus would be the maximum excess player i can achieve by leaving player j given an allocation, $\boldsymbol{x}$, as shown in Equation (2.25).

$$s_{i,j}(\boldsymbol{x}) = \max \{e(S, \boldsymbol{x}) \mid S \subseteq N, i \in S, j \notin S\} \tag{2.25}$$

The surplus could therefore be interpreted as player i's bargaining power over player j, in terms of reducing the set of opportunities for player j. If $s_{i,j}(\boldsymbol{x}) > s_{j,i}(\boldsymbol{x})$, the incentives for i leaving j is stronger, and vice versa if $s_{i,j}(\boldsymbol{x}) < s_{j,i}(\boldsymbol{x})$.

Several allocations may satisfy the above equations (known as *the kernel*). In order to find one unique allocation (the nucleolus), the next stage would be to decrease the dissatisfaction of the second most dissatisfied subcoalition. This process continues until a single allocation remains. In turn, the lexicographically[8] smallest excess vector is obtained. One could think of this iterative process as something similar to adding cuts to an optimization problem, as depicted for the three-player barycentric diagram in Figure 2.19.

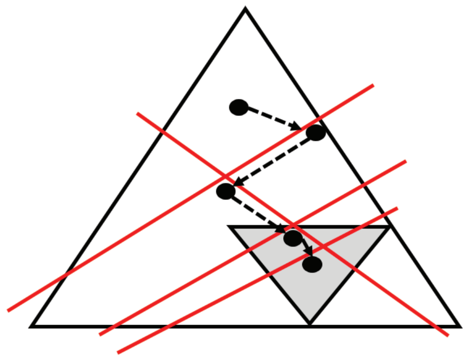


Figure 2.19: Illustration of the nucleolus algorithm that iteratively add cuts/restrictions (red lines) to the optimization problem for minimizing excess payoffs. The resulting allocation will be 'the most stable one', and in the core given that it is non-empty (grey shaded area).

First, the excess definition in Equation (2.24) is inserted into the core (Equation (2.23)), and an equivalent excess-core can be derived as follows in Equation (2.26):

$$C(N, v) = \{\boldsymbol{x} \in X \mid e(S, \boldsymbol{x}) \leq 0 \text{ for all } S \subset N\} \tag{2.26}$$

Hence, for a solution to be in the core one would like to minimize ε to be zero, or negative. Consequently, the above assertion could be recast as shown in Equation (2.27) using the more restrictive core, $\varepsilon < 0$, called the ε-core, $C_\varepsilon(N, v)$. Even if the core does not exist, this is useful in terms of finding the 'closest to core' solution by relaxing $\varepsilon > 0$.

$$C_\varepsilon(N, v) = \{\boldsymbol{x} \in X \mid e(S, \boldsymbol{x}) \leq \varepsilon \text{ for all } S \subset N\} \tag{2.27}$$

By exploiting this, one could iteratively decrease ε till the ε-core becomes empty. At this point, the most stable solution is obtained, meaning that the dissatisfaction cannot be decreased more for the subcoalition with highest excess. If there are multiple possible payoffs at this point, one could iterate to the next step including these and minimize ε-core among those, yielding the second least core. Note that the previously most dissatisfied subcoalition is not included in this process because it has already been minimized. This is illustrated with the red lines in Figure 2.19 and continues until there is only one unique allocation left. The result will be in the kernel and bargaining set, meaning that the players have no bargaining power over each other. The nucleolus is always inside a non-empty core, and hence provides a stable grand coalition.

8. To sort lexicographically means that vectors could be sorted in the same manner as words are alphabetically sorted.

The nucleolus can be found by solving lexicographically extended linear min-max problem (Risanger et al., 2018), based on (Behringer, 1981). Equation (2.28) shows the resulting optimization problem that has to be solved iteratively, k times, incorporating constraints that ensures the smallest excess (2.28b), ε_k, and group rationality (2.28c). The maximum excesses of previously binding coalitions, ε_j, are maintained with Equation (2.28d), where j represent previous iterations $\{1, \ldots, k\}$. Subcoalitions that have been binding are included in the set F_j. The first iteration will therefore have $F_1 = \emptyset$. The constraint (2.28b) considers only the subcoalitions that have not yet been binding.

$$\min \quad \varepsilon_k \tag{2.28a}$$

$$\text{s.t.} \quad v(S) - \sum_{i \in S} x_i \leq \varepsilon_k \qquad \forall S \subset N \text{ and } S \notin F_k \tag{2.28b}$$

$$\sum_{i \in N} x_i = v(N) \tag{2.28c}$$

$$v(S) - \sum_{i \in S} x_i = \varepsilon_j \qquad \forall S \in F_j, j \in \{1, \ldots, k\} \tag{2.28d}$$

$$\varepsilon_k \in R, x_i \in R \qquad \forall i \in N$$

If the dual variables for (2.28b) are non-zero, its corresponding subcoalition is binding. Hence, which coalition to include in F_k is known. Algorithm 3 shows the iterative process of solving the nucleolus for a game. We can terminate the process when the allocation is unique. This is the case if Equations (2.28c) and (2.28d) form n linearly independent restrictions.

Algorithm 3 Iterative calculation of the nucleolus

initialize Previously binding subcoalitions $F_1 = \emptyset$
initialize Vector of previous maximum excesses, $\boldsymbol{\varepsilon}$
initialize Iteration $k = 1$
while $\boldsymbol{x}_{nu}$ not unique **do**
    solve LP problem (2.28) for iteration k
    Append objective ε_k to vector of previous maximum excesses, $\boldsymbol{\varepsilon}$
    if (2.28c) and (2.28d) contain n linearly independent restrictions **then**
        Solution is unique and $\boldsymbol{x}_{nu} = \boldsymbol{x}_k$
    else
        for all Dual variables of constraints (2.28b) from the solution of iteration k **do**
            if Dual variable not zero **then**
                Corresponding S added to F_{k+1}
            end if
        end for
        $k = k + 1$
    end if
end while
return $\boldsymbol{x}_{nu}$

A cooperative investment fund using Power Purchase Agreements

One alternative to achieve any of the suggested allocation schemes from cooperative game theory is to initially support the development of new transmission interconnections using one of the conventional allocation approaches and then implement a mechanism to facilitate side payments that would result in the desired allocation of net benefits over the planning horizon. However, it is not clear if such mechanism would be implementable in practice. For instance, for the NSOG case the main limitation is that it involve large transfers of net benefits among countries — ranging from €80m to €2300m — *before* these benefits are even realized (Kristiansen et al., 2018). Upfront, lumpy payments of this size may not be very welcoming for any stakeholder.

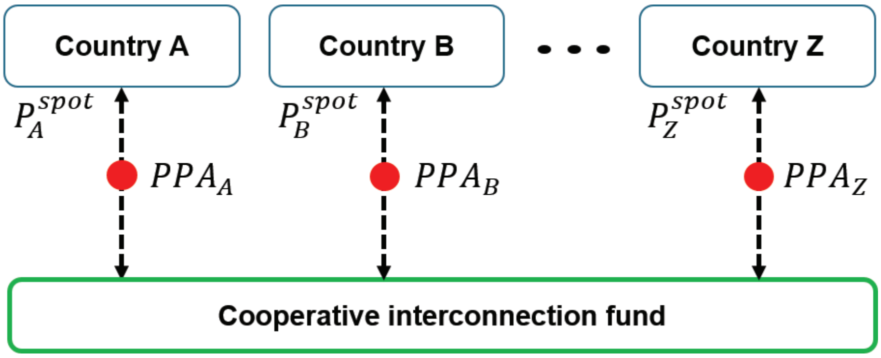


Figure 2.20: A cooperative interconnection fund based on Power Purchase Agreements (PPAs). A country importing/exporting at an interconnection pays/receives the PPA price for the given transmission corridor. Illustration from Prof. Francisco Muñoz's presentation at INFORMS 2018.

As countries trade power over time one could instead implement of a set of Power Purchase Agreements (PPAs) and a *cooperative interconnection fund*. Under this mechanism, the cost of new transmission interconnections and congestion rents could be initially divided through a conventional mechanism, such as the ESP or the PNBD. A coordinating organization (e.g. , ENTSO-E or ACER) could then estimate the required side payments to achieve a fair allocation of net benefits under the SV or nucleolus. This set of side payments could be used as a basis for defining a set of PPAs, as contracts for differences, between the interconnection fund and each country in the region.

Consider the following contractual agreement. Say PPA_A is the (fixed) contract price for country A, L_A is the set of transmission interconnections to neighboring countries of A (both new and existing), $P_{l,t}^{spot}$ is the hourly price at the node where line l is connected to country A (border node), $f_{l,t}^{exp}$ and $f_{l,t}^{imp}$ are the hourly power flows that, respectively, go out and into country A through line l (both are non-negative), and $loss_l$ is a loss factor. If country A sells its power (i.e., if $f_{l,t}^{exp} > 0$ and $f_{l,t}^{imp} = 0$) at a fixed price equal to PPA_A but collects $P_{l,t}^{spot}$ for every MWh of power exported through line l, then this country must receive a side payment from the interconnection fund equal to $(PPA_A - P_{l,t}^{spot}) \cdot f_{l,t}^{exp}$ if $PPA_A > P_{l,t}^{spot}$. On the other hand, if $PPA_A < P_{l,t}^{spot}$, then country A must pay a compensation to the interconnection fund equal to $(P_{l,t}^{spot} - PPA_A) \cdot f_{l,t}^{exp}$. The opposite is true if country A imports power at a certain hour (i.e., if $f_{l,t}^{imp} > 0$ and $f_{l,t}^{exp} = 0$). Summing over all transmission interconnections connected to country A, L_A, and over all representative hours in the planning period T (e.g. , 8760 hours in a representative year), we can compute the side payment to country A, denoted SP_A, as follows:[9]

$$SP_A = a \cdot \sum_{l \in L_A} \sum_{t \in T} (PPA_A - P_{l,t}^{spot}) \cdot (f_{l,t}^{exp} - f_{l,t}^{imp} \cdot (1 - loss_l)) \tag{2.29}$$

If $SP_A > 0$, country A will receive a side payment , otherwise, if $SP_A < 0$, A will pay an economic compensation to the interconnection fund. Given an estimate of SP_A, it is possible to find the value of PPA_A such that, over time, country A will ultimately achieve a desired allocation of net benefits. This could be applied to all countries in the region to define the set of PPAs that achieve the desired final allocation of net benefits under the SV. Note that if C denotes the set of countries in the region, then:

$$\sum_{c \in C} SP_c = 0 \tag{2.30}$$

This is true because, by construction, side payments are only welfare transfers among countries to achieve the SV. In the mechanism design literature this property is known as *budget balancedness* (Narahari, 2014).

9. The parameter a denotes an annuity factor used to compute the discounted sum of annual side payments over the 30-year planning horizon.

2.3.2 Tradespace exploration

A potential caveat with expansion planning is the concentrated focus on the modelling itself. In turn, central questions related to problem structuring (Keeney, 2009; Belton & Stewart, 2010), objectives (Keeney, 1982, 1996), and value tradeoffs (Cohon, 2013) become less important. To this end, this section aims at shading more light on the latter topics in order to set a broader context for what concerns expansion planning. Methods from systems engineering is leveraged for this purpose, and particularly the framework known as Responsive System Comparison (RSC) (Ross, McManus, Rhodes, Hastings, & Long, 2009). This includes techniques such as multi-attribute tradespace exploration and multi-epoch analysis which, as we will see later, has strong ties to operations research.

The general idea behind the RSC framework is to *"take a designer or system analyst (RSC practitioner) through a step-by-step process of designing and evaluating dynamically relevant system concepts"* (Ross et al., 2009). In short, this means that the problem is broken into different stages; (i) information gathering, (ii) alternatives evaluation, and (iii), alternatives analysis, as illustrated by Figure 2.21. As the figure suggests, this sequential process would include thinking about what a decision maker (and potential stakeholders) would like to achieve, what is considered valuable and how it is affected by different system components, and finally what the resulting alternatives are.

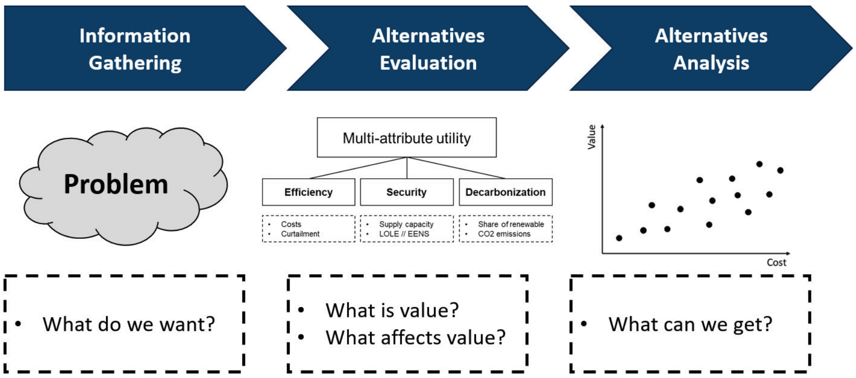


Figure 2.21: Conceptual approach for problem structuring and exploration under the Responsive System Comparison (RSC) framework. From left; how to design the problem, to assessing different value functions, to exploring alternatives.

Evaluation of design alternatives: What is value?

Clearly determining the value, or objectives, is essential in terms of finding good solutions. However, this part may be very difficult to do with high precision. For example, how should we aggregate the efficiency, reliability, security, and eco-friendliness of a TEP solution into one overall score? In what unit should this score be? And how should we discount future measures to get a present value? Traditional TEP problems take a monetary approach in line with microeconomics, where the interest is to maximize welfare, by internalizing externalities adding, e.g. , a CO_2 tax and a penalty cost per hour of downtime. An alternative approach could be to transform the value attributes, e.g. efficiency or reliability, to a utility function representing the preferences to the relevant stakeholder, or multiple stakeholders (Fitzgerald & Ross, 2016), in line with multi-attribute utility theory (Keeney, 1996). However, each of these approaches need a proper

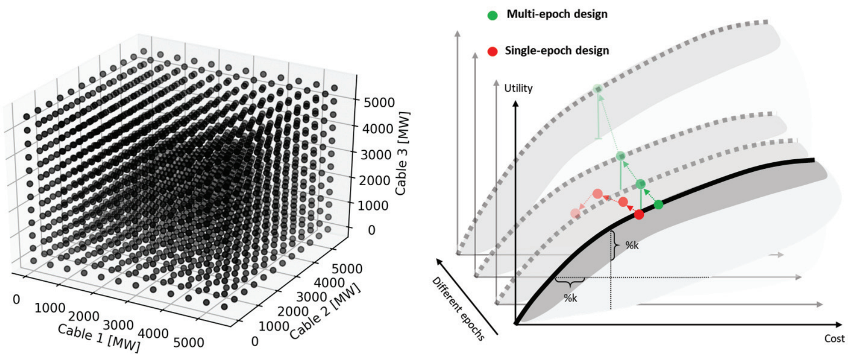


Figure 2.22: A discretization of model variables (left) makes it possible to explore different system designs (right). Depending on the tradespace axes, an efficient design would be located at the Pareto front (solid black line) or within its fuzzy region (light grey). In turn, a scenario specific, optimal design (red dot) might not prove efficient in other scenarios, contrary the a multi-epoch/scenario, optimal design (green dot).

representation of the constituent attributes, and a proper insight on how to discount future values to trade them off against the short term.

Tradespace exploration: One solution among many mutually beneficial ones?

Optimization programs requires a well-defined representation of the problem, but for opaque problems this may not exist. Thus, instead of optimizing an oversimplified and incorrect representation of reality to find “the best solution”, it can be valuable to explore multiple solutions and try to gain insights about the problem and alternative solutions. The latter could be of particular importance for, e.g. , analysts and management decision makers. Also, by visually exploring alternative one could easier communicate the benefits of one solution over another. This draws a parallel to set based design (Singer, Doerry, & Buckley, 2009), as multiple solutions are assessed at the same time and options are kept open before specifications and tradeoffs are more fully understood. In general, we want to explore the main tradeoff between values and costs -– i.e. what can we possibly get from invested resources? Furthermore, what are the tradeoffs between the competing value attributes for a given cost? Such questions are addressed in research related to MATE (Ross & Hastings, 2002; Ross, Diller, & Hastings, 2003).

A tradespace is simply the space of trades, i.e. the space of possible design alternatives (Ross et al., 2009). A tradespace plot is thus a discretization of the design space as illustrated with Figure 2.22. Here, three decision variables are discretized uniformly spanning their potential values (left part) which, in turn, are simulated with a model to explore the solution space and tradeoffs (right part). The power of evaluating a tradespace in contrast to only a set of optimal solutions, is invaluable for insights to the problem at hand.

Epoch-era analyses: Robust designs under changing context and needs

To more flexibly use scenarios in exploratory design analyses, the epoch-era framework was developed (Ross & Rhodes, 2008). Epoch-era analyses branches into two subgroups; epoch analyses and era analyses. The epoch representations are particularly useful for tradespace exploration, as one could explore sets of alternative designs in specific epochs. That is, for a given context and needs, analogous to the short-term in microeconomics (Varian, 2014). However, in the long-term, both context and needs can change. Eras represent the long-term and are constructed by chains of epochs. Eras could thus be thought of as stages in a temporal scenario tree (Pflug & Pichler, 2014), allowing analyses of lifecycle performance of systems and their exposure to uncertainty.

The right part in Figure 2.22 illustrates the concept of fuzzy Normalized Pareto Trace (fNPT) which is used to identify certain designs that performs at the k% fuzzy Pareto front in multiple epochs (green dots), compared to single epoch optimal designs (red dots). The k%, as indicated with the dark grey area in Figure 2.22, determines the size of the fuzzy Pareto front. For instance, $k = 0\%$ represents the true Pareto front, while $k = 2\%$ allows for 2% deviation from the true Pareto front in relative size of the tradespace. The fNPT is a measure of how often one particular design is within this predefined k% fuzziness Pareto front, where $fNPT = 1$ means that the design in question is at the fuzzy Pareto front in all epochs considered. Contrary, if $fNPT = 0$ the design does not occur at the k% fuzzy Pareto front in any of the considered epochs. For instance, a solution that performs well in Epoch 1 might not perform as good in, e.g. , Epoch 4, so the fNPT might equal 0.5 since the design lays at the fuzzy Pareto front in only half of the epochs. Thus, the objective would be to identify designs with a small k% as possible and high fNPT.

Chapter 3

Contributions

“ ”

Marshall McLuhan, *We shape our tools, and afterwards our tools shape us.*

The preceding chapters presents the key motivations and challenges for decision support if face of future power system development. In addition, relevant methods for an expansion planning model, like the ones developed during the course of this PhD project, were discussed. To this end, the scene is set for summarizing the contributions from this research. For the sake of consistency, recall the contributions listed in the end of the introduction chapter, i.e. :

C1 Developed customized models for multinational TEP in an open source environment, programmed with Python (and the optimization library; Pyomo). Both a deterministic and a stochastic optimization model, generic for multistage investment decisions.

C2 Case studies of a future, potential North Sea offshore grid using transparent, open-source data for year 2030. Main topics include flexibility needs and the role of interconnectors in market environments with varying shares of renewables (e.g. offshore wind), other flexibility providers (e.g. hydro, storage, gas, demand), artificial offshore wind power hubs (Power Link Island), and uncertainty (e.g. generation mix).

C3 Demonstrated the added value of applying methods from statistics, game theory, and systems engineering – all in context of TEP. This to reduce model dimensionality, account for bargaining power and estimate the value of efficient/fair payoffs/incentives, and systematically untangle complexities related to alternative solutions and tradeoffs.

Apart for the general assertions listed above, a more detailed discussion is provided in the remainder parts of this chapter. First on main articles followed by those that are considered to be supplementing articles. The latter is primarily dedicated for articles that does not comply with the three-folded structure of this thesis, i.e. (i) pre analytics, (ii) model development, and (iii), post analytics, but that still are relevant.

3.1 Main articles

These articles are listed into their respective methodological categories, although individual papers might comprise a mix. This includes dimension reduction techniques, case studies on flexibility needs in the North Sea area, planning under uncertainty, how to combine optimization and system engineering, and how to calculate an efficient allocation of net benefits in order to support efficient investments at a multinational scale.

3.1.1 Sampling and clustering of input data

There are two papers that fits this category; paper A and paper B. The first one introduces a set of different sampling and clustering techniques including a case study of model implications, i.e. the impact on expansion planning for an offshore grid in the North Sea. The second is a continuation of the latter, with a focus on model sensitivity. That is, to assess whether the different dimension reduction techniques performs consistently well over a range of different model parameters. To this end, the goal is to evaluate the degree of model dependency.

Paper A: Assessing the impact of sampling and clustering techniques on offshore grid expansion

Due to the ongoing large-scale connection of variable renewable energy sources (VRES) to the power systems, short- to long-term planning models are challenged by an increasing level of variability and uncertainty. A key contribution of this article is to explore and assess the implications of different dimension reduction techniques for long-term Transmission Expansion Planning (TEP) models. For this purpose, a selection of sampling and clustering techniques are introduced to compare the resulting sample errors with a variety of sampling sizes and two different scaling options of the original data set. Based on the generated samples, a range of TEP model runs are carried out in order to investigate their impacts on investment decisions and market operation. Here, with a case study reflecting offshore grid expansion in the North Sea region for scenario incorporating data for year 2030. The results shows that dimension reduction techniques performing well in the sampling and clustering process does not necessarily produce reliable results in the large-scale TEP model.

Key Takeaways

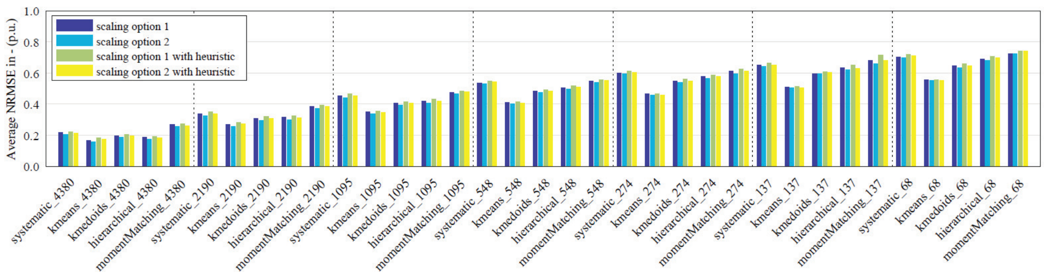


Figure 3.1: The performance of different sampling methods in relative terms to the full data set, for different sample sizes. The more samples, the lesser difference from the full data (Härtel, Kristiansen, & Korpås, 2017). Normalized Root Mean Square Error (NRMSE).

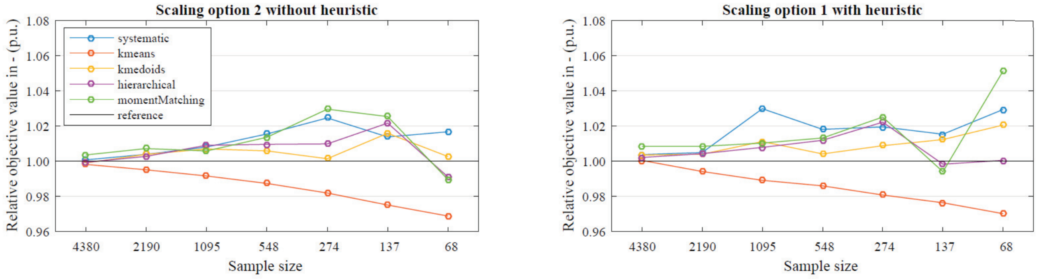


Figure 3.2: The model performance of different sampling methods in relative terms to the model output based on the full data set, for different sample sizes ans scaling options (Härtel, Kristiansen, & Korpås, 2017). For a high sample size, all techniques yields about the same objective values, which is close to 1 p.u..

The analysis suggests that the dimension reduction techniques may score very well in terms of capturing distributions or error measures such as the presented Normalized Root Mean Square Error (NRMSE) in Figure 3.1, but that the output from the TEP model employing the samples yields different score patterns in terms of investment and operational costs for a potential future offshore grid, as shown in Figure 3.2. Takeaways include:

- A 50% reduction in number of hours considered for time series analysis yields a 80% decrease in model simulation time – while, at the same time, obtaining solutions ±1.5% from the reference case (relative to the objective value for base case).
- Good performing techniques in the sampling process does not necessarily produce reliable results when being applied to a large-scale TEP model, which became particularly evident for k-means clustering. See Figure 3.1 and Figure 3.2.
- Agglomerative hierarchical and k-medoids clustering demonstrates comparatively good results when quantifying both the NRMSE and the effects on TEP model output.
- Benchmarking sampling and clustering methods on statistical moments might contradict its true performance in terms of the results obtained with a TEP model. For instance, in TEP, capturing extreme values might be more important that representing data points close to the mean.

There are a few assumptions and limitations to be kept in mind when discussing the results obtained in the comparisons above. For instance, short- to long term inter-temporal constraints, such as seasonal hydro reservoir continuity (or storage in general), are not accounted for in the model. At the same time, however, this assumption facilitates the sampling and clustering of individual hours because the chronology of the original time series data can be ignored. With this in mind, the following is recommended for future work:

- Use of sophisticated heuristics, particularly for investment models as they significantly depend on the highest occurring values in the original data sets. That is, it might be the high price differences that creates incentives for grid expansion.
- Incorporate inter-temporal constraints to better capture medium-term dynamics and the operational flexibility in TEP models.

- Investigate model dependent sampling methods or alternative strategies involving decomposition of the full year problem.

Paper B: Sensitivity analysis of sampling and clustering techniques in expansion planning

Short and long-term power system planning models are becoming more complex due to the underlying objective of capturing current and future market characteristics as detailed as possible. Partly because of more variability, uncertainty, and integration of geographically spread market areas. Dimension reduction methods can be used to keep the planning models tractable, e.g. time series sampling and clustering, but they represent a trade-off between model complexity and level of detail. The accuracy of dimension reduction methods can be measured both in terms of raw data processing and model output metrics, where the latter reveals how well a sampling technique fits that particular model instance. In this study, the robustness of several sampling and clustering techniques is quantified with different model instances. The instances are created by independently varying model parameters, such as the marginal cost of generation. As the obtained findings indicate that the performance of the considered techniques is, indeed, model-dependent, more insight into the performance of common dimension reduction techniques in power system planning applications is provided. The results are illustrated with a case study of the North Sea Offshore Grid (NSOG), using a bi-level mixed-integer linear optimization program. All things considered, systematic sampling and moment matching are shown to give the most robust results from the sensitivity analysis.

Key Takeaways

There are patterns in Figure 3.3 that are of particular relevance. First, notice the small deviations that occur for reductions in marginal costs and for -50% CO2 price. Most of these cases yield robust results by not deviating too far from the full-year benchmark, leading to about the same level of investments. As those parameter reductions mainly impact thermal units, one explanation could be that arbitrage opportunities are cancelled out due to small price differentials between market areas bordering the NSOG. Hence, there is limited room for deviations in investment strategies. In turn, this could also explain the opposite effect that becomes obvious for increased marginal costs and increased CO2 prices, since those scenarios consistently result in under-investments. That is, there might be more investment opportunities than what the model manages to identify with the reduced time series data.

Other takeaways include:

- A sensitivity analysis revealed that the results are highly model dependent due to the variability of results (rankings) from different model instances.
- The most robust techniques were systematic sampling and moment matching for the North Sea Offshore Grid case study. One reason for this might be the fact that the more sophisticated clustering techniques build clusters in which the most extreme data points are represented by a cluster centroid.
- Results indicate that some parametric sensitivities have more local than global impacts in operation conditions in the TEP model — with recurring effects in the investment strategies.

With the above in mind, the following is recommended for future research:

- Investigate model-dependent dimension reduction techniques since these might lead to more robust solutions than the most common, model-independent techniques that are investigated in this study.

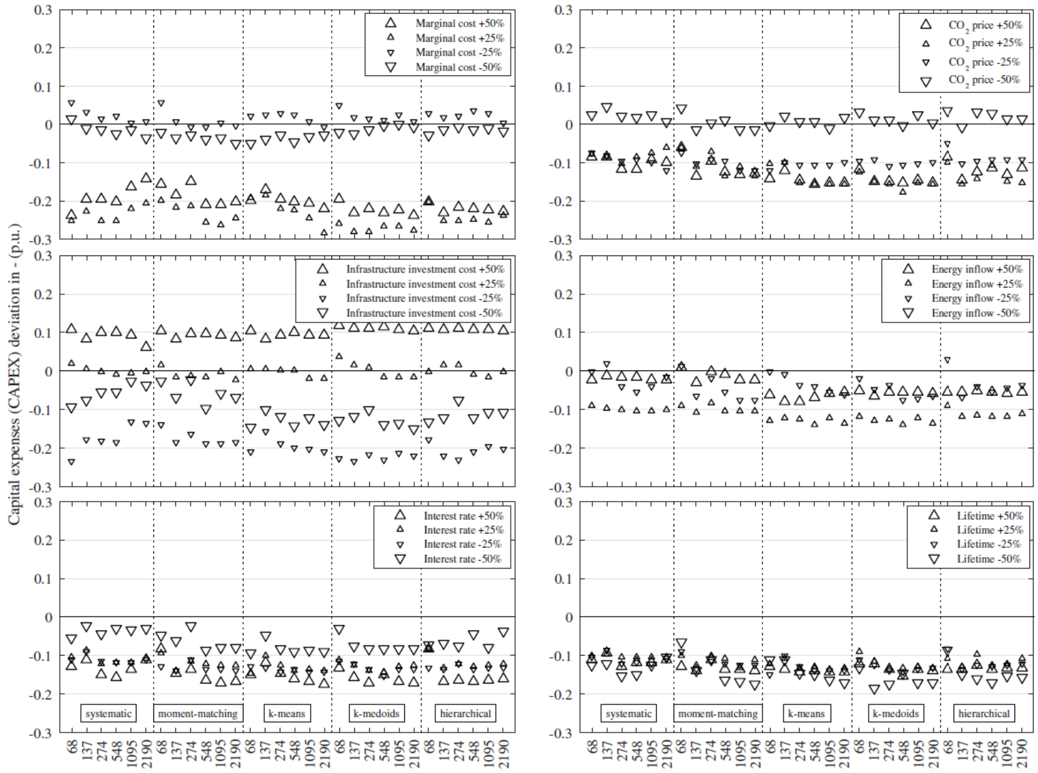


Figure 3.3: Results showing capital expenses (CAPEX) performance when varying six different model parameters, each with five different sampling and clustering techniques and sample sizes varying from 68 to 2190 times steps. The performance is measured in relative terms to a full-year analysis and labelled with upward- and downward-facing triangles indicating the direction of sensitivity parameter change with the size indicating the level of change.

- Methods of particular interest include importance sampling, in combination with principal component analysis. That is, start by exploiting model results in order to identify time steps and what technologies that explains the most variation in the results.

3.1.2 The role of North Sea Offshore Grid as flexibility provider

There are four articles that appeals to this category on flexibility. This includes one paper that explains the use of numerical weather data to represent VRES at, e.g. , geographical coordinates with no historical data and subsequently how this play out in the expansion planning model (Kristiansen et al., 2016). To this end, grid is evaluated in an environment where both pumped hydro storage (PHS) and demand side management (DSM) are present. The second paper (Kristiansen et al., 2018b) presents the concept of a power link island (PLI) and to which extent this adds value to the system. The latter is extended into a third paper (Kristiansen et al., 2018a) with more focus on assessing the value of a PLI, or meshed grid typology, under different typologies and generation mixes. Finally, the fourth paper (Kristiansen et al., 2018) studies the geographical demand for different flexibility providers and assess their value by exploiting desirable properties of cooperative game theory.

Paper C: Introducing system flexibility to a multinational transmission expansion planning model

Grid investments are considered as sunk costs with a very long lifetime, particularly in an offshore grid context. The market mechanisms for cost recovery of these investments are exposed to an increasing share of variable power generation at the supply side, demanding more flexibility in the system. Hence, it is of particular interest to account for these changes in tools being used for decision support. This paper presents an extension of an already existing mixed integer linear program (MILP) for transmission expansion planning (TEP), by including system flexibility in the form of energy storage and demand-side management. Moreover, an enhanced description of variable power generation is used to construct production profiles with a higher level of detail. The latter is achieved by simulating weather data for wind and solar incorporating higher temporal and spatial resolution than in previous studies. The impact of using these times series for variable power generation, and the introduction of system flexibility, are both presented separately using the North Sea area for a comparative case study with 2030 scenarios provided by ENTSO-E. The consequent results of interest include lifetime operational costs (OPEX), investment costs (CAPEX), and offshore wind power curtailment.

Relevant contributions are:

- Quantify the impact on transmission investments of using simulated, hourly production profiles from two different numerical weather data sources. One with higher temporal- and spatial resolution than the other.
- Introduce alternative flexibility options, such as pumped hydro storage and demand side management, in order to assess its impact on grid investments as competitors in providing flexibility to the system as a whole.

Key Takeaways

- Time series for VRES with higher temporal resolution (COSMO EU) than previously used (Reanalysis) resulted in peak values for a shorter period of time. In turn, the model interpreted this as less availability of peak feed-in and consequently higher OPEX and lower CAPEX, as this is important for grid dimensioning.
- Increased PHS capacity in NO lead to more grid investments as a result of its valuable temporal flexibility.

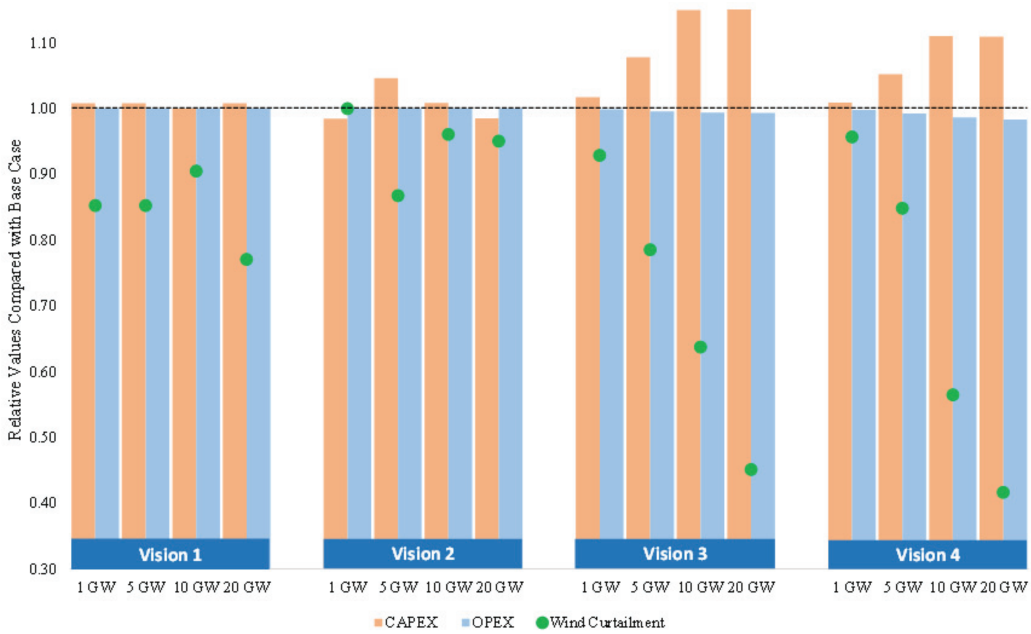


Figure 3.4: The impact of substituting fractions of the hydropower capacity in Norway with pumped hydro storage (PHS), under different scenarios for year 2030 (Vision 1 - 4). All in relative terms with respect to a base case (without PHS) for CAPEX (orange bars), OPEX (blue bars) and curtailment of wind power generation (green dots). CAPEX is related to transmission grid investments that becomes profitable as more capacity is allocated to PHS, rather than conventional hydropower.

- Curtailment of offshore wind power is significantly reduced when harvesting additional interconnection- and PHS capacity, ranging from 5% to 60% reduction from base case.
- The marginal value of PHS diminish as its capacity increases and, consequently, curtailment from VRES decreases.

Recommendations for future research:

- As many alternative flexibility options show their largest potential within a time frame of a few contiguous hours, the impact of accounting for longer consecutive periods of sample hours needs to be assessed in the future.
- The dynamic effects of DSM can influence the investment decisions even more if they are an integral part of the TEP model.
- To determine whether energy storage could be detrimental for grid investments, or not, the PHS case should be implemented for a net energy importing area as a comparison with the net exporting case studied here (i.e. Norway).

Paper D: Towards a fully integrated North Sea Offshore Grid — An engineering-economic assessment of a Power Link Island

An increasing share of variable power feed-in is expected the next decades in the European power system, with a considerable offshore wind potential in the North Sea region. This demands more temporal- and spatial flexibility in the system, and an adequate grid infrastructure can provide both. This article presents an engineering-economic approach evaluating the impact of novel infrastructure designs towards a fully integrated North Sea Offshore Grid (NSOG), including TenneT's vision of a Power Link Island (PLI). A PLI is an artificial island for transnational power exchange and distribution of offshore wind resources. We introduce the concept and evaluate the economic benefits and system implications under three different case studies incorporating 2030 scenarios from ENTSO-E. The results demonstrate system cost savings up to 15.8% when comparing a fully integrated PLI solution with traditional, radial typologies. The PLI did in general result in more efficient system dispatch of wind resources, where the involvement from Norway, Great Britain, and Germany occurred most frequently in terms of grid reinforcements and expansions. The contribution is twofold:

- Establishing a foundation for future research on offshore grids incorporating economies of scale of a PLI.
- Quantify the added value of a fully integrated PLI under different scenarios.

Key Takeaways

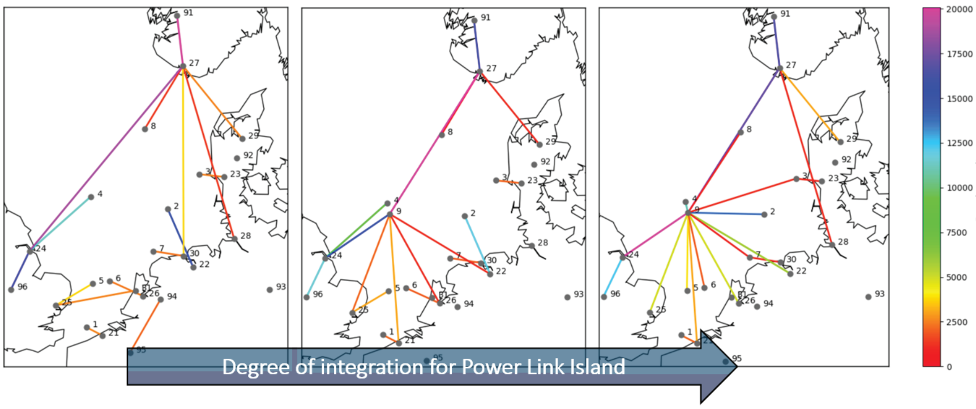


Figure 3.5: Resulting grid expansions when moving from Scenario A (left plot) to Scenario C (right plot), i.e. from radial towards fully integrated, meshed typology including a PLI as a multinational hub for both cross-border exchange and offshore wind power distribution. Illustrations are based on Vision 1.

The concept of a Power Link Island (PLI) is introduced with a cost amounting to approximately €1.5bn (TenneT, 2017a). That is, the cost for the island itself, in the same way as for traditional platforms, but with a maximum capacity amounting to 30 GW. Costs for power electronics at the island are indirectly accounted for with new cables being built, meaning that the total costs for transformers and power electronics most likely will be over-estimated as the model will invest in more equipment than necessary. Thus, economies of scale are only accounted for in terms of construction, and not equipment nor maintenance benefits. The main takeaways from this study includes:

- The PLI demonstrated significant value in a scenario with high shares of VRES, yielding up to 15.8% cost savings compared to the benefits obtained with a radial typology.
- Key countries for exploiting the benefits of a PLI were identified to be NO, GB, and DE. Meaning that the dynamics between these countries, and the PLI, represents the majority of the value potential for a PLI.
- Wind sites that are directly connected to the PLI require less grid investments than for cases where the same wind capacity is allocated onshore, to different countries. This because the PLI is able to exploit a higher utilization of grid investments, in addition to better wind resources.
- Additional wind capacity, beyond the base scenario, leads to more efficient utilization near the PLI in comparison to being allocated onshore, to different countries.

Future research suggestions:

- Building 10 to 15 transmission lines in parallel is unlikely to get public approval, particularly for onshore grid reinforcements. Thus, a study with more realistic capacity constraints per transmission corridor could be useful.
- Identify the most robust transmission corridors as a result of incorporating uncertainty in, e.g. , offshore wind capacity, investment costs, and/or location.
- Perform a sector-coupled analysis since the PLI is visioned to be in close proximity to gas infrastructure. To this end, production and export of hydrogen could be a possibility.

Paper E: Economic and environmental benefits from integrated power grid infrastructure designs in the North Sea

The North Sea Offshore Grid (NSOG) is considered an important contributor towards large-scale integration of renewables and electricity market coupling. Different typologies have been studied for such a multinational power grid, ranging from radial point-to-point connections to more integrated and meshed typologies. An artificial island enables a high level of integration of both offshore wind power and transnational trade due to economies of scale. This paper present multiple case studies of the Power Link Island (PLI) which is visioned by TenneT in the Doggerbank area. Our results demonstrate that the capabilities of such an island could add significant value to the system as a result of more efficient use of geographically spread, cost-efficient resources. However, depending on the future level of grid integration and generation mix, the added value of a PLI varies between €0.15bn to €20bn. Consequently, this could result in 18% more efficient utilization of renewable resources, primarily offshore wind, and significant reductions of CO2 emissions. Key contributions to this end includes:

- Demonstrate the added value of a PLI as a prominent solution to facilitate for transnational trade and offshore wind power distribution.
- Sensitivity analysis with respect to different portfolios of generation mix and grid infrastructures.

Key Takeaways

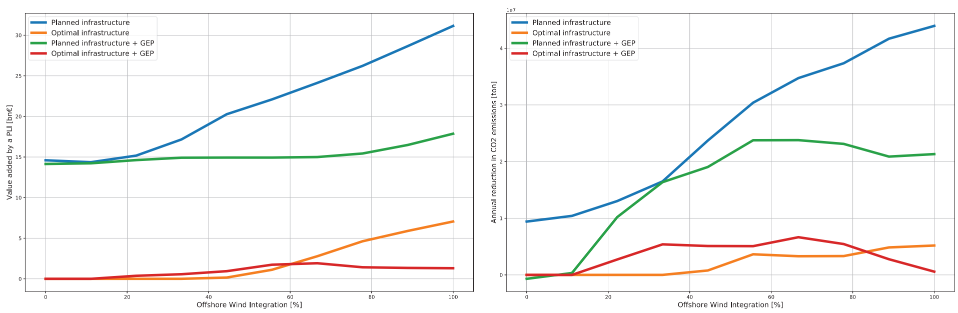


Figure 3.6: The added value of a PLI under an increasing share of OWP, ranging from 0 GW to double the capacity, as compared to the original input data from ENTSO-E Vision 4 (i.e. 130 GW). The added value is quantified for different underlying system designs, in term of cost savings (left plot) and CO_2 emission reductions (right plot).

- Two distinct futures are used to assess the value of a PLI — (i) with planned infrastructure and generation mix (blue line in Figure 3.6) and (ii) with optimal infrastructure and optimal generation mix (red line in Figure 3.6).
- With the above, the most pessimistic and optimistic bounds for the benefits of a PLI is set to €0.15bn and €21bn, respectively, in a scenario with high shares of VRES (ENTSO-E Vision 4).
- The marginal reductions in CO_2 emissions, due to a PLI, are significant when the offshore wind capacity is increased from zero to 65 GW (with reductions around ~12-26 million

tonCO$_2$ per year). In comparison, the current installed offshore wind capacity is 11.2 GW (Pineda, 2018).

One of the main challenges for a PLI and its surrounding infrastructure to materialize is related to (i) the caveat of quantifying benefits over a long lifetime with models of reality, and (ii), that benefits are potentially distributed unevenly in the magnitude of billions euros. Economic principles of fairness and stability could help to solve the latter, but with the need for mechanisms to balance these deviations out as power is traded between countries over time.

Paper F: A generic framework for power system flexibility analysis using cooperative game theory

Electricity grid infrastructures provides valuable flexibility in power systems with high shares of variable supply due to its ability to distribute low-cost supply to load centers (spatial), in addition to interlinking a variety of supply and demand characteristics that potentially offset each others' negative impact on system balance (temporal). In this paper, we present a framework to investigate the benefits of alternative flexibility providers, such as fast-ramping gas turbines, hydropower and demand side management, by using a generation and transmission capacity expansion planning model. We demonstrate our findings with a multinational case study of the North Sea Offshore Grid with an infrastructure typology[1] from year 2016 and operational data for year 2030 — considering a range of renewable capacity levels spanning from 0% to 100%. First, we show how different flexibility providers are allocated geographically by the model. Second, operational cost savings are quantified per incremental unit of flexible capacity. Finally, we present a way to rank different flexibility providers by considering their marginal contribution to aggregate cost savings, reduced CO_2 emissions, and increased utilization of renewable energy sources in the system. The Shapley Value from cooperative game theory allows us to assess the latter benefits accounting for all possible sequences of technology deployment, in contrast to traditional approaches. This framework could help to gain insights that are relevant for energy policy designs or risk assessments.

Key Takeaways

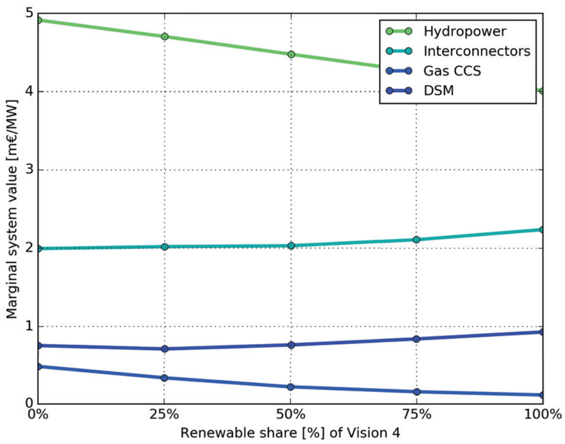


Figure 3.7: The marginal value per unit capacity (m€/MW) for each flexibility provider in terms of operational cost savings at system level.

The analysis reproduce similar observations found in the existing literature. For instance, grid expansion is shown to be the most prominent option due to its facilitation for increased availability of spatial flexibility, and consequently temporal flexibility from other providers that are geographically spread. In turn, this yields a positive impact on the utilization of VRES and, through a more cost-efficient operation, also system cost savings. Moreover, by exploiting the properties of the Shapley Value (SV), one could support the claims of grid being the most robust flexibility provider. Without further elaboration, these are the main takeaways:

1. Typology encompass a mix of topology and technology.

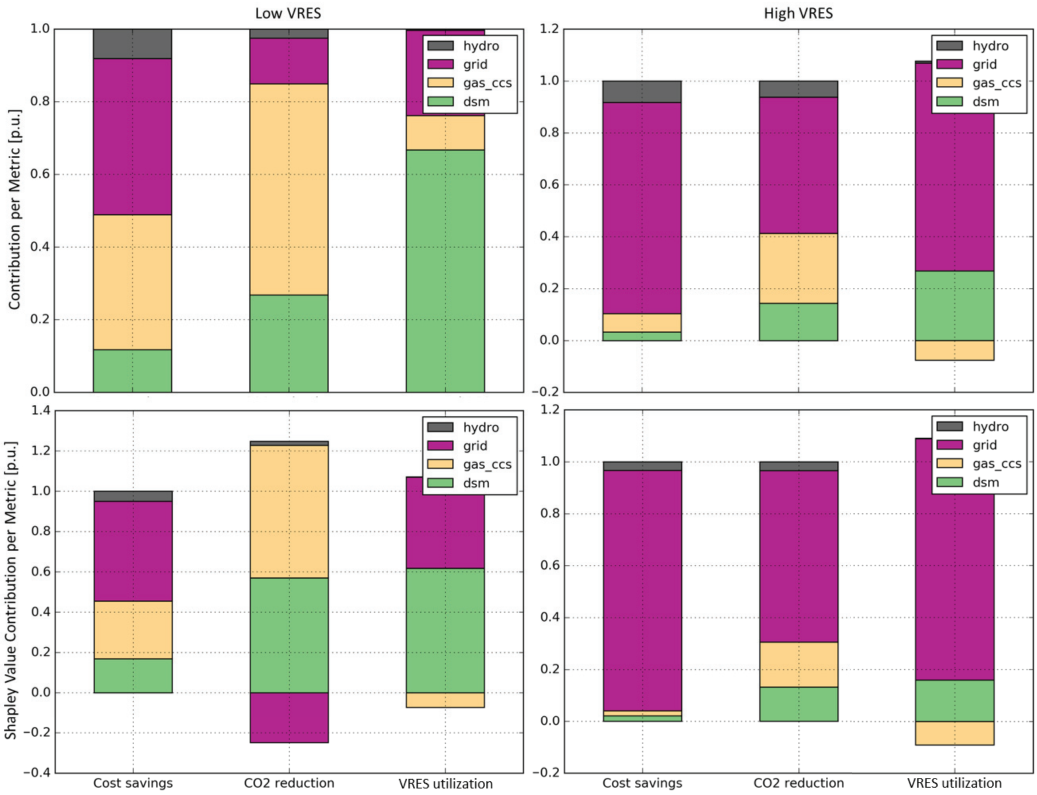


Figure 3.8: Relative benefit contribution to the system in terms of cost savings, reduced CO_2 emissions, and increased utilization of renewable supply (reduced curtailment). The upper two plots shows the implicit value added by each technology option (traditional approach), while the lower two plots shows the value added for a range of possible deployment sequences (Shapley Value). Both for low- (left) and high (right) levels of VRES.

- This framework could easily be reproduced with more detailed planning models or market simulators, incorporating a detailed representation of unit commitment, storage, and load flow equations.
- The demand for flexibility is to a large extent covered by grid ($\sim 50\%$) and fast-ramping gas turbines ($\sim 40\%$) on average, across all countries.
- Geographically, the isolated flexibility demand is highest for DE and GB. There is a considerable demand for grid expansion in connection with NO, GB, and DK.
- The marginal value is highest for Hydropower as a flexibility provider, followed by grid. However, the former is artificially high due to constraints on hydropower expansion.
- The Shapley Value reveals that a traditional assessment of flexibility providers might undervalue the contribution from grid expansion with 6% and 22% in terms of cost savings and VRES utilization, respectively.

Power system flexibility is investigated over a range of variable renewable energy source (VRES) capacity levels, ranging from 0% to 100% of the 2030 scenario “Vision 4” by ENTSO-E. The use of a fictive thermal unit allows for approximation of availability of both capacity and yearly energy inflow over this range of VRES capacities, yielding comparative analytics. Also, note that investment costs are ignored, meaning that the resulting values can be regarded as break-even thresholds. The Shapley Value does, for instance, implicitly account for the disadvantages of long lead time or the advantage of learning rate, e.g. the long lead time of grid investments and future cost-efficient DSM solutions, respectively. This because of its sequential characteristics, i.e. the value of each technology is evaluated in all possible deployment sequences.

The following is recommended for future research:

- A possible extension could be to use a stochastic model to calculate characteristic functions for the Shapley Value, and compare this with the deterministic one. This would reveal to which extent that the Shapley Value mange to incorporate uncertainty, given its combinatorial calculation scheme.
- Use dynamic investment models. In this paper, we incorporate different sequences for deployment but ignore the discounted monetary value with respect to the time between different deployments.
- Marginal contributions calculated with SV are based on bulky capacity investments. This means that each technology is not deployed partially, but in full scale determined by the expansion model. With Aumann-Shapley (AS), it is possible to capture the marginal contribution at fractional levels.

3.1.3 Planning under uncertainty

Paper G: Multistage grid investments incorporating uncertainty in offshore wind development

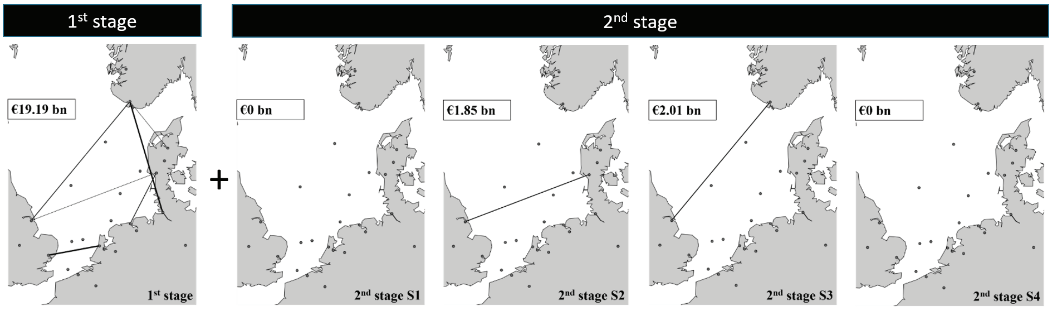


Figure 3.9: Grid investments are undertaken in two stages; namely stage one before information about future wind capacities are known, and after five years, in stage two, when one of four different scenarios for offshore wind has been revealed. To this end, the planner has the option to postpone risky investment decisions.

Representation of uncertainty in transmission expansion planning (TEP) models has become increasingly important as many power systems are exposed to significant technological changes induced by top-down climate and energy targets. The objective with this paper is to incorporate uncertainty regarding future offshore wind deployment and allow for two investment stages for grid expansion, where the second stage provides valuable flexibility for a system planner. A stochastic two-stage mixed-integer linear program is used for this purpose, applied to a case study of the North Sea Offshore Grid (NSOG).

Key Takeaways

With the given data and assumptions, these are the main findings:

- The planner can benefit €1.72 bn (0.40 %) with perfect forecasts about future wind capacities (i.e. Expected Value of Perfect Information (EVPI)).
- By endogenously accounting for uncertainty about future wind capacities, a 'forward looking planner' could gain €22.30 m (0.0052 %), in comparison with the best deterministic approach (i.e. Value of a Stochastic Solution (VSS)).
- Allowing for multiple investment steps as countries trade power over time result in the option to postpone investments as uncertainty is revealed. To this end, modular flexibility is estimated to be worth €22.41 m (i.e. Real Option Value (ROV)).
- A forward-looking planner is willing to invest in more capacity than in a expected value, deterministic case.

These results are obtained from a case study with an already strong infrastructure in place as a base case, and when only considering uncertainty in wind capacity. This will naturally limit the aforementioned metrics listed above. In addition to investigating the latter in more detail, the following extensions are recommended for future research:

- Introduce a lead time for investment decisions, e.g. construction time after a decision is undertaken.
- Allow for generation expansion to respond to transmission investments (i.e. proactive planning).
- Vary the number of investment stages and lead time in order to quantify managerial characteristics of different investment options. For instance, renewable generation might increase short term variability/uncertainty, but do their relatively short lead time and modular properties reduce long term uncertainty relative to more capital intensive technologies with longer lead time?

3.1.4 A fair allocation of costs and benefits

If not the most important (published) contribution from this thesis, this section focuses on the cost-benefit allocation problem of international grid investments. This have not gotten as much attention in academia, yet, despite being a very important research topic in context of ensuring efficient investments in a multinational context.

Paper H: A mechanism for allocating benefits and costs from transmission interconnections under cooperation — A case study of the North Sea Offshore Grid

This paper propose a generic mechanism for allocating the benefits and costs that result from the development of international transmission interconnections under a cooperative agreement. The mechanism is based on a planning model that considers generation investments as a response to transmission developments, and the Shapley Value from cooperative game theory. This method provides a unique allocation of benefits and costs considering each country's average incremental contribution to the cooperative agreement. The allocation satisfies an axiomatic definition of fairness. We demonstrate our results for three planned transmission interconnections in the North Sea and show that the proposed mechanism can be used as a basis for defining a set of Power Purchase Agreements among countries. This achieves the desired final distribution of economic benefits and costs from transmission interconnections as countries trade power over time. We also show that, in this case, the proposed allocation is stable.

Key Takeaways

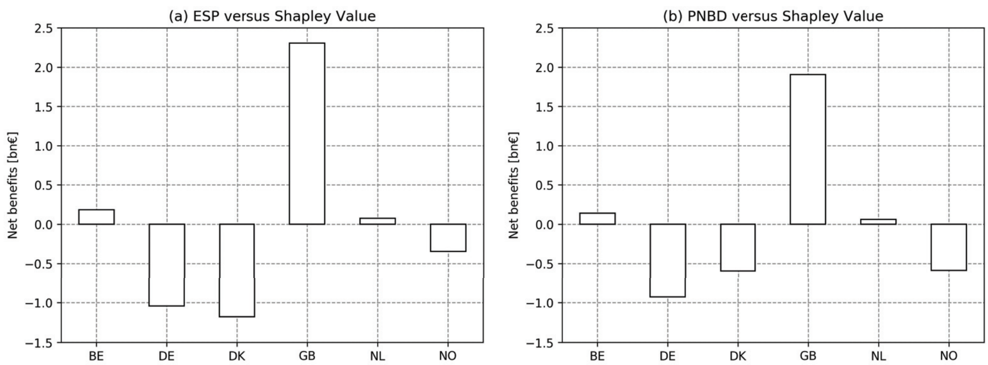


Figure 3.10: Relative differences of net benefits per country when comparing the (a) Equal Share Principle (ESP) and the (b) Positive Net Benefit Differential (PNBD) with respect to the Shapley Value. Positive values indicate that countries are overcompensated relative the SV allocation (Kristiansen, Muñoz, Oren, & Korpås, 2018).

With a thorough introduction to economics of expansion planning, the paper clearly demonstrates how one could utilize a bi-level equilibrium model to identify efficient investments and, in combination with cooperative game theory, find mechanisms that ensure that all countries have an inventive to support a set of projects identified by the model. In summary, these are the main takeaways:

- The Shapley Value provides a unique allocation of benefits, considering veto power of each country.

- It is shown that traditional allocation schemes significantly over- or under estimate what is considered a 'fair' allocation, as suggested by the SV. This is illustrated for ESP and PNDB in Figure 3.10, which are neither fair nor stable allocations.
- By leveraging bargaining theory for group rationality or properties for convexity, one could easily assess whether the SV allocation is stable, or not. That is, that no countries have incentives to deviate from a cooperative solution.
- Power Purchase Agreements (PPAs) could help facilitating for side-payments as countries trade power over time. For this study, annual payments amounting €170m would be necessary, which is not too far from the already existing inter-TSO compensation (ITC) fund mechanism (∼€258m).

Recommendations for future research:

- Investigate the allocation problem using a stochastic program to identify a set of efficient investments, and compare with the deterministic case. Is bargaining power less evident in stochastic solutions? Does the difference between SV and traditional allocation methods converge (closer) towards zero for stochastic solutions?
- Investigate different PPA calculations. In this case, there is one price for trades in both directions. Other alternatives include (i) one price for each direction, (ii) different prices for different transmission lines between two countries, and (iii), adaptive PPAs with respect to time in order to meet financial limitations and/or a changing market landscape.

3.1.5 Tradespace exploration

Paper I: Combining optimization and tradespace exploration as decision support for transmission expansion planning

A set of methods from the systems engineering community is introduced to an increasingly active area in operations research, namely transmission expansion planning (TEP). A majority of conventional TEP models relies on black box optimization programs with the objective of minimizing total system costs or maximizing welfare. In such cases, a limited number of solutions are provided and consequently insufficient insights about the main value tradeoffs. To aid with this problem, we leverage techniques such as multi-attribute tradespace exploration and multi-epoch analysis to systematically untangle problem complexities and gain valuable insights. In combination with a mixed-integer linear program that co-optimize investments and market dispatch for a power system, we investigate different high-level solutions for a future North Sea Offshore Grid. Our case study comprise international stakeholders and serves as a good example for similar multi-stakeholder planning problems. The value of leveraging this multidisciplinary framework for decision support is clearly demonstrated with comparisons to operations research. As an example, by leveraging the visual strength of tradespace exploration one could efficiently map optimal solutions from an optimization program within a space of alternative solutions. Consequently, valuable information can be gained about the problem itself, tradeoffs to other solutions, and solutions' performance under changing contexts and needs. From this, parallels are be drawn to the literature on deterministic and stochastic optimization. Finally, one could raise awareness of subjectiveness by clearly defining the boundaries for potential solutions.

Key Takeaways

From the presented MATE framework, one of the main benefits is clearly the aspect of visually evaluating tradeoffs among multiple value attributes without relying on any heuristics (black box). That is, an "optimal solution" calculated by an optimization program can have multiple "neighbouring" solutions with considerable variations in value tradeoffs. For instance, one design yielding the maximum welfare ("optimal") might be surrounded by other solutions performing almost as good in terms of welfare but with more desirable performance in terms of, e.g. , CO2 emissions or security of supply.

- The value of combining tradespace exploration and optimization is demonstrated with a case study considering the expansion of three multinational transmission corridors in the North Sea Offshore Grid (NSOG).
- It is shown that this approach is suitable for problems with a relatively low number of decision variables, both in terms of tractability (number of simulations needed) and traceability (from performance to design).
- Parallels are drawn to the optimization literature where the performance of optimal, deterministic solutions are visually shown over multiple epochs (scenarios), including the intuition of value-robust solutions. That is, solutions that perform better over all considered scenarios which is also the case for optimal, stochastic optimization programs.
- General observations such as the tradespace structure yields an intuition about the nature of the problem – e.g. how additional renewables (Vision 4) play out in the solution space and to what extent this might require better decision-making tools.
- Mapping solutions from an optimization program into the tradespace generates visual insight and allows for multi-objective tradeoff (MATE) analysis.

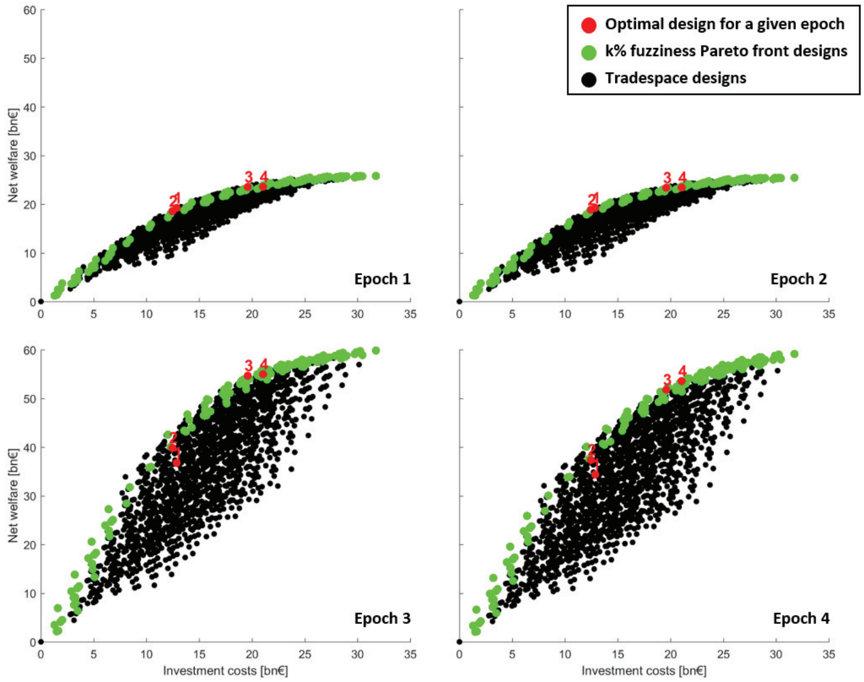


Figure 3.11: Tradespace exploration for different epochs, i.e. Vision 1 – 4. Black dots represent the overall tradespace (solution space), while green dots represent designs that are within the 2% fuzzy Pareto front. The four red dots are 'optimal designs' calculated by the optimization program with a labeled numbering spanning 1 – 4, indicating which vision it is calculated with respect to.

- The use of tradespace could be invaluable for assessing utility functions since those might not uniformly exists for multinational systems such as the one presented here. That is, using the tradespace in a constructive way to ask decision makers and stakeholders about what they want and help them form priorities could serve an important part of the planning problem.

Recommendations for future research:

- There are relevant aspect of RSC that could be investigated in more detail, such as the definition of value and utility as this study is not based on stakeholder interviews.
- The view of a multi-stakeholder perspective is an interesting extension, using the tradespace to visualize different stakeholders' contribution to system welfare — which could serve as a supplement to cooperative game theory studies questioning to which extent different stakeholders contribute and how costs and benefits should be allocated.
- Regarding the discretization of decision variables, and thus the tractability in terms of reasonable simulation times, there is more work to be done in doing efficient discretization and parallelization of the TEP model simulations. For instance, one could use the TEP

model to map important sample intervals which in turn could decrease the number of necessary simulations.

- Study whether stochastic optimization programs suggest designs that are within a certain range of % fuzzy Pareto front across multiple scenarios.

3.2 Supporting articles

In addition to the main articles mentioned in previous section, there are also other papers that are considered relevant. This includes work together with master students and SINTEF Energy.

Initial NSOG studies

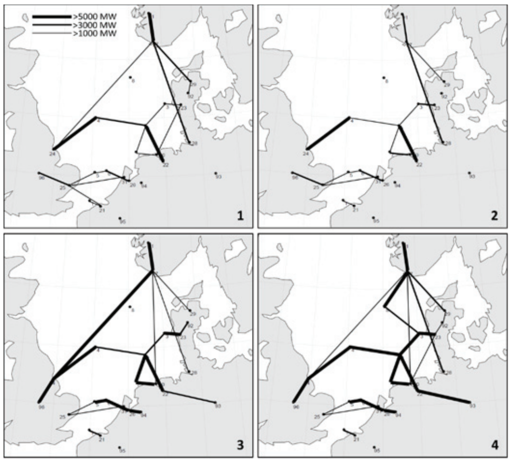


Figure 3.12: AC and HVDC infrastructure investments for ENTSO-E's Vision 1 to 4. Thickness of the lines reflect the capacity investment levels at each transmission corridor.

In (Kristiansen et al., 2015), we present a case study quantifying the impact of four different scenarios on transmission capacity investments. The ENTSO-E's four visions for 2030 are implemented as input data to evaluate the potential impact that these might have on the optimal offshore grid infrastructure, as depicted with numbering one to four in Figure 3.12. From this, relevant findings include:

- Infrastructure investments vary in the range of €10bn to €32bn, with the highest discrepancies arising between Vision 2 and 4 in terms of investments.
- Isolated price areas, such as GB, are exposed to higher variations in the degree of investment levels, depending on which scenario that materialize.
- Higher shares of VRES induce more grid investments due to flexibility needs.
- Figure 3.12 shows that GB and NL are exposed to significant investment needs, for a meshed grid solution, in order to integrate the offshore wind capacity.

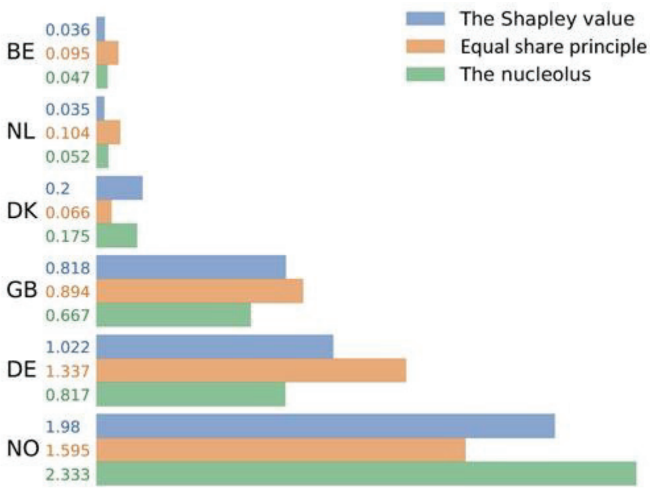


Figure 3.13: Comparison of the three different allocation methods for grid investments in the NSOG using ENTSO-E Vision 4 (Risanger, Kristiansen, Munoz, & Korpås, 2018). Net benefits are given in bn e, where the Shapley Value could be interpreted as 'most fair' and the nucleolus as 'most stable'.

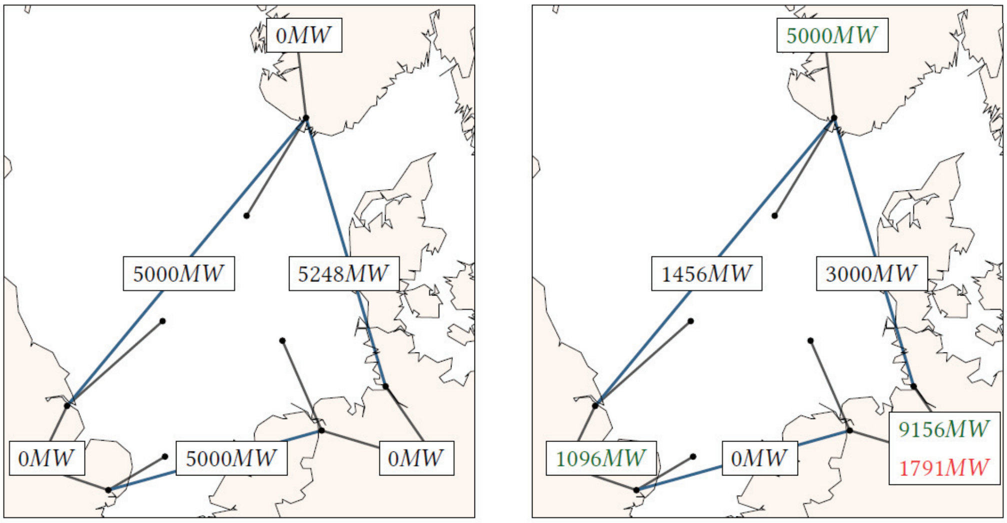
Strategic investments and the cost benefit allocation problem

A continuation from (Kristiansen et al., 2018) was carried out in both (Risanger et al., 2018) and (Risanger et al., 2018), investigating principles of fairness, bargaining power and stability in context of multinational infrastructure investments. To this end, the kernel and nucleolus were introduced and compared with the Shapley Value. All from cooperative game theory. From this set of contributions, the following assertions are derived in context of this thesis:

- Three different allocation methods are investigated to support efficient welfare investments in systems where a supra-national planner is absent, namely; (i) the Equal Share Principle, (ii) the Shapley Value, and (iii), the nucleolus. Each of which represents different degrees of fairness and stability.
- The results demonstrates the properties and benefits of the different methods, which could yield valuable insights on what concerns fair allocations, national bargaining power, and incentives to cooperate for the greater good (system optimal designs).

Allocation methods that suggests payoffs deviating from the material costs and benefits (i.e. from investments and market operation) will require side payments. These side payments could take place in form of Power Purchase Agreements (PPAs), as suggested in (Kristiansen et al., 2018). But what is the value of such and allocation scheme and accompanying side payment mechanism? In (Risanger, 2018), a three-level hierarchical investment model is developed in order to answer this question. To this end, the following is relevant:

- The upper level (UL) in the three-level hierarchy comprise multinational infrastructure investments with the objective to maximize system welfare, subject to the intermediate level (IL) and the lower level (LL). The IL represents national expansion planning maximizing



(a) Centrally performed investments

(b) Strategically performed investments

Figure 3.14: Capacity expansion under the cooperative (a) and non-cooperative (b) model. Interconnection capacity expansion labelled at branches, and generation expansion labeled at countries' load center with green being VRES and red non-VRES. Source: (Risanger, 2018).

welfare. Both subject to the LL, i.e. system operation for the purpose of cost-efficient supply of electricity in the system.

- Karush-Kuhn-Tucker (KKT) conditions are derived in order to represent optimality upwards in the optimization hierarchy — yielding mathematical problems with equilibrium constraints (MPECs) and a equilibrium problem with equilibrium constraints (EPEC).
- Non-convex complementary constraints and bi-linear terms are linearized in order to recast the equilibrium model as a mixed-integer linear program (MILP).
- Results indicate that international transmission investments are less attractive when individual countries rather expand domestic generation capacity. However, this is strongly driven by the fact that only consumer surplus is included in the intermediate levels objective functions at this stage.
- The difference in objective function between the cooperative (system optimization) and non-cooperative (three-level) represent the value of a fully functioning allocation scheme (in this case $\sim$ 15% total cost savings) — given that the non-cooperative model yield the most realistic, strategic outcome (i.e. what we believe would happen without a cooperative mechanism).

The latter is still an ongoing study with a particular focus on linearization techniques that allows us to 'easily' include producer- and consumer surplus into the intermediate level objective functions. The predecessor of this work originated from another master's thesis (Bjerketvedt, 2017), where fundamental differences in market modelling was investigated. That is, everything between a monopoly to perfect competition in context of power markets. The latter demonstrated, among other things, the following:

- Price impact of imperfect competition — highest for monopoly and lowest for perfect competition.
- Increased market power leads to decreased willingness to invest in additional capacity (keep margins high).
- Investment levels varies between different market designs e.g. Monopoly, Cournot, and Stackelberg.
- The intraday price peaks increase when energy storage plays strategically by withholding capacity, and the magnitude is increased even more when production capacity is restricted.

From all the above, one could argue that large-scale investment models that assume perfect competition would probably over-invest compared to what seemingly might be more realistic. Again, in order to reach system optimal designs, adequate allocation mechanisms for cooperation have to be in place.

Power flow modelling

In (Åmellem et al., 2016), a comparative study quantifying the effects of different power flow modelling techniques is presented. Two approaches are considered, namely; (i) a flow based (FB) modelling leveraging power transfer distribution factors (PTDFs) to represent DC load flow, and (ii), net transfer capacity (NTC) with the caveat of disregarding loop flows. The benefit with the former, compared to DC load flow equations, is that the dimensionality of the optimization model is kept at a minimum since phase angles can be ignored (which otherwise would have been variables). To this end, to following takeaways are relevant in this context:

- The studies were carried out under the four ENTSO-E 2030 Visions, outlining the future development of the European power system.
- The NTC approach indicates that Norway serves the role of providing balancing power to the Continent.
- While in a PTDF approach a re-dispatch of power flows indicates that Norway acts as a power transportation hub to, and from, the Continent and Great Britain.
- In the FB case, the total power flow in the system is increased as well as investments in new grid capacity.
- FB modelling is more computational demanding and requires that the PTDF-matrix is updated when new transmission capacity is added to a branch (or new branches).

Chapter 4

Conclusions

> “ ”
>
> Peter Senge, *Systems thinking is a discipline for seeing wholes. It is a framework for seeing interrelationships rather than things, for seeing 'patterns of change' rather than static 'snapshots'.*

This thesis presents research on transmission expansion planning, i.e. the problem of deciding when, where, and at what capacity to build power system infrastructure. There is a particular focus on international investments as this is becoming increasingly important in face of future power system development plans. This is especially true for Europe and the North Sea area with the intention of harvesting renewable resources over a larger geographical area, integrate markets, and increase security of supply. To this end, the work presented here investigates (i) problem structuring (key aspects, objective(s) and tradeoffs), (ii) modelling approaches, (iii) computational challenges, and (iv), barriers related to implementation of projects (country-level bargaining power, incentives, and perception of fairness). The North Sea Offshore Grid is used as a case study to demonstrate the latter assertions, including the potential value of offshore (and onshore) grid expansion in the North Sea region.

A majority of this research originates from model development, including exploration of alternative methods that could increase insights to the core problem at hand; transmission expansion planning. A Python-based optimization model has been developed, named PowerGIM, which is available at BitBucket.org in the same repository as PowerGAMA – a pan-European power market simulator developed by Sintef Energy. PowerGIM encompass a generic structure that can assemble both deterministic- and stochastic model instance(s), exploiting the capabilities of the optimization modelling library, Pyomo. Additionally, hierarchical (strategic) programming and decomposition techniques are investigated and discussed in light of PowerGIM.

Aside from the underlying modelling work, the thesis follows a three-folded breakdown of a thought expansion planning work flow; (i) pre analytics, (ii) model development and analyses, and (iii), post analytics. In brief, these relates to (i) acquiring and pre-processing data, (ii) using optimization- and/or equilibrium programs to model perfect/imperfect power markets with, and without, uncertainty, and (iii), assessing a set of investments in context of exploring alternatives and tradeoffs, including ways to support international cooperation for the most efficient set of investments (but with insufficient incentives). All case studies are ran using open source data, predominantly data that replicates “Vision 4”. This is the most ambitious scenario derived by the European Network for Transmission System Operators for Electricity (ENTSO-E) in terms of variable renewable energy sources (VRES).

Pre analytics

First, hourly and variable production profiles for rural areas that are located far from load centers might be difficult to obtain. This could be a result of nonexistent historical data, which is the case for many offshore wind sites. Instead, numerical weather data could be used to simulate production profiles for a given coordinate and installed capacity. A general observation to this end is that operational costs tends to get higher, the higher the temporal resolution is for this data. This is particularly true for systems with a high share of VRES, since peak feed-in is being overestimated with less granular data, both hourly (power) and over time (energy). In turn, simulated price differences between adjacent countries maintain a shorter duration and consequently lower congestion rents (i.e. weaker signals for transmission investments) when using more granular data.

Second, tradeoffs between granularity and size of input data is investigated, comparing multiple clustering and sampling methods. Model simulation time is reduced with $\sim 80\%$ when using input data half the size of the original, full year data set. Moreover, one should carefully choose at which stage the performance of the latter methods is quantified — comparing statistical moments of different sets of input data or model results. In fact, k-means clustering was shown to be the best performing clustering technique when comparing input data metrics, while this was not the case when considering how these sampled data sets played out in the model. A sensitivity analysis revealed that the latter results could be very model dependent, and that systematic sampling induced the least variance and the most consistent performance.

Model development and analyses

The role of a grid infrastructure is thoroughly discussed, including important modelling aspects such as physical- and temporal details, proactive planning, and uncertainty. The main focus in the paper contributions is, however, the former — the role of grid as a flexibility provider in the North Sea area, including its impact on surrounding countries.

First, it is shown that grid proves strong when comparing it with other large-scale flexibility options such as pumped hydro storage (PHS), demand side management (DSM), and/or fast-ramping gas turbines. There are at least two reasons for this; (i) it provides spatial flexibility in terms of interlinking a diversified set of generation technologies, storage, and demand, and (ii), which in turn leads to increased utilization of temporal flexibility. For the NSOG, it is shown that a potential competitor of the same scale, such as PHS, is not detrimental for the value of grid. In fact, the most likely location for new PHS capacity, which is Norway, is expected to induce a higher demand for grid investments in transmission corridors to the Continent and to Great Britain. In terms of capacity, grid covers about $\sim 50\%$ of the flexibility demand in the North Sea area, in which Germany and Great Britain represents a majority of this demand.

Second, the same holds when assessing the performance of different flexibility providers in a combinatorial deployment sequences, i.e. revealing the impact of one technology being deployed before, or after, another. To this end, the Shapley Value from cooperative game theory shows that the value added by grid could potentially be 6% and 22% undervalued in terms of cost savings and VRES utilization, respectively, when comparing with traditional analyses.

Third, different typologies of a NSOG infrastructure are evaluated. That is, different combinations of topology and technology such as, e.g. , radial (point-to-point) and meshed grid designs.

The concept of a power link island (PLI) is investigated as a visioned, meshed alternative with considerable economies of scale due to its capacity, compared to traditional meshed solutions. Again, key players are identified as Norway, Great Britain, and Germany, with a PLI spanning the estimated added value of €0bn to €21bn, depending on the underlying grid typology and generation mix. Assuming that the planned infrastructure materialize by year 2030, it is shown that a PLI could harvest offshore wind resources efficiently ($\sim 18\%$ less curtailment and up to 26 million ton CO_2 emission reductions per year) in addition to facilitating for increased cross-border trade.

Fourth, by incorporating uncertainty in future offshore wind capacity levels it is shown that a supra-national grid planner could potentially gain €1.72bn under perfect foresight (value of perfect information). That is, in terms of cost savings for the system as a whole. Of this, an endogenous modelling of uncertainty is expected to be worth €22.30m (expected value of stochastic solution). Moreover, the option to postpone investments as uncertainty materialize into known information, additional €22.41m could be gained (expected real option value). In this capacity, it is demonstrated that the latter forward-looking planner is generally willing to invest more, compared to deterministic cases, in order to hedge against the expected cost of not doing so.

Post analytics

The first topic is related to the cost benefit allocation problem. Here, the goal is to identify optimal sets of investments and quantify (i) the materialized allocation of net benefits from market operation, and (ii), allocation schemes with varying degrees of fairness and stability. The former is defined as the equal share principle (ESP) or the positive net benefit differential (PNBD), depending on how costs are allocated, while the latter could be derived from cooperative game theory using e.g. the Shapley Value (SV), Aumann-Shapley (AS), or the nucleolus. Findings from this study demonstrate that the SV provides a unique allocation that satisfies economic principles of fairness, while the nucleolus is designed to find solutions that are more stable –- in terms minimizing the dissatisfaction among players. Moreover, methods to assess stability of a cooperative agreement is presented, such as checking for group rationality and/or convexity (supermodularity). As these allocations requires side payments, a cooperative investment fund is suggested to help facilitate for a re-distribution of net benefits as countries trade power over time. This is done by calculating prices for power purchase agreements (PPAs) between countries and the fund. As this framework induce annual payments in the same range as the already existing inter-TSO compensation (ITC) fund, it is expected to be highly feasible as it is both (i) relatively simple, and (ii), dynamic in terms of deriving different PPA contracts –- which could be anchored to one or many market conditions (also changes over time).

Second, more emphasis is dedicated to generating insights to the transmission expansion planning problem. For this purpose, a set of methods from systems engineering is used to systematically structure the problem at hand and to visualize potential grid designs and tradeoffs. This approach has traditionally been applied to planning problems with no clear, or multiple (and potentially conflicting), objective(s). From the perspective of operations research, there are some parallels that could be drawn; (i) between multi attribute tradespace exploration (MATE) and deterministic optimization, and (ii), between multi-epoch analysis and stochastic optimization. A third analogy could also be envisioned between MATE and bargaining theory, in which bargaining power could be visualized for a set of players in a space of alternative designs. Hence, it stands to reason that the combination of advanced optimization programs and MATE could be valuable in terms of providing insights about (i) model complexity, (ii) alternative solutions and tradeoffs, and (iii), value functions that could help decision makers prioritized objectives by first seeing how these might play out and affect each other.

4.1 Recommendations for future work

There are many case specific recommendations for future work that are mentioned in this thesis. Aside from the more obvious ones, such as incremental model enhancements, general recommendations are summarized below.

On input data and dimension reduction, a low-hanging fruit and interesting contribution for the community would be to investigate the degree of model dependency of different sampling and clustering methods. One possibility is to use principal component analysis to identify which variables that explains the most variation in model output. This could also allow for some form of systematic, model dependent sampling to be incorporated into the analysis. Also, a distinction between models with and without intertemporal constraints would be of particular interest in order to reveal if some methods are better suited for one or the other. Furthermore, the two model categories could be assessed with deterministic and stochastic model instances, creating four sets of categories in total. One immediate challenge would be consistent clustering, i.e. deciding which clusters that best represent all scenarios. The latter is not an issue when only considering one scenario, as the clustering algorithm sees one set of capacities.

Regarding uncertainty, an interesting extension would be to vary the degree of lead times (i.e. duration between decision to the first date of an asset being operative) and the number of possible investment stages (i.e. points in time when the planner is exposed to the option of investing). To this end, one could demonstrate the managerial benefits of short lead time, which is the case for most VRES technologies such as solar PV. For instance, maybe VRES tend to increase short term uncertainty (variability) but reduce long term uncertainty compared to conventional technologies such as coal. This, somewhat counter-intuitive, statement would be very interesting to quantify, in addition to demonstrating core capabilities of multistage stochastic programming and possibly the benefits of different decomposition methods (exploiting the structure of coupling constraints versus coupling variables). In particular, the performance of stochastic dual dynamic integer programming which, as far as the author is aware, has mostly been applied to hydropower scheduling models.

There is also an array of possibilities to investigate in the allocation problem space, and in particular within cooperative game theory. In this thesis, players were assumed to reach a grand coalition but what happens if it fails to form? Are there ways to accommodate for multiple coalitions? That is, are there allocations that would guarantee a particular set of subcoalitions to be formed in a fair manner? Also, are there any evident patterns that could be drawn when using two sets of characteristic functions; from (i) a deterministic model, and (ii), a stochastic model. Moreover, investigation of multilateral grid investments such as for the power link island would add an interesting dimension to the allocation problem. Without making the list of possibilities too long, a final recommendation would be to assess different PPA calculations. For instance, one price per transmission corridor, two prices per corridor (per direction), and/or dynamic prices over time with respect to (a) changing market conditions and/or (b) different discount factors (preference for when side payments are made).

Finally, planning for development of the power system can potentially be more interlinked with other energy sectors such as heat and transportation. This could yield alternative sets of efficient grid investments due to changes in the underlying flexibility needs. For instance, loads might not only be supplied with other energy sources but also offer itself temporal flexibility in terms of storage and/or smarter consumption. Hence, a multi-sector expansion planning model could be essential in identifying efficient investments for such potential, future systems.

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Chapter 5

Papers

Paper A

Härtel, P., Kristiansen, M., and Korpås, M. (2017). Assessing the impact of sampling and clustering techniques on offshore grid expansion planning. *Energy Procedia*. 14th Deep Sea Offshore Wind R&D Conference, EERA DeepWind'2017, *137*.

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Assessing the impact of sampling and clustering techniques on offshore grid expansion planning

Philipp Härtel[a,*], Martin Kristiansen[b], Magnus Korpås[b]

[a]*Energy Economy and Grid Operation, Fraunhofer IWES, Königstor 59, 34119 Kassel, Germany*
[b]*Department of Electric Power Engineering, NTNU, O. S. Bragstads plass 2E, 7034 Trondheim, Norway*

Abstract

Due to the ongoing large-scale connection of non-dispatchable renewable energy sources to the power systems, short- to long-term planning models are challenged by an increasing level of variability and uncertainty. A key contribution of this article is to explore and assess the implications of different dimension reduction approaches for long-term Transmission Expansion Planning (TEP) models. For the purpose of this study, a selection of sampling and clustering techniques are introduced to compare the resulting sample errors with a variety of sampling sizes and two different scaling options of the original data set. Based on the generated samples, a range of TEP model runs are carried out to investigate their impacts on investment strategies and market operation in a case study reflecting offshore grid expansion in the North Sea region for a 2030 scenario. The evaluations show that dimension reduction techniques performing well in the sampling and clustering process do not necessarily produce reliable results in the large-scale TEP model. Future work should include ways of incorporating inter-temporal constraints to better capture medium-term dynamics and the operational flexibility in power system models.

Keywords:
Transmission Expansion Planning, Sampling, Clustering, Dimension Reduction, Offshore grids

1. Introduction

1.1. Increasing variability and uncertainty in TEP models

Most power systems around the world experience an increasing share of variable and non-dispatchable generation in their energy mix. At the same time, adequate models for both short-term and long-term planning become more complex. In comparison to traditional power systems which were primarily subject to power demand variations and fault occurrences, introducing high shares of renewable sources yields a significant rise of the power systems' underlying variability and uncertainty [1].

* Corresponding author. Tel.: +49 561 7249-471; fax: +49 561 7249-260.
E-mail address: philipp.haertel@iwes.fraunhofer.de

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Determining investments in new transmission lines or reinforcements of the existing transmission network is a crucial task in power system planning. These investment decisions are lumpy and capital intensive, which can have a long-lasting effect on expected market prices and power system operations. For this reason, the task of making sensible Transmission Expansion Planning (TEP) decisions is a widely studied problem [2].

The TEP is particularly relevant in the European context, where the European Union is pursuing a fully integrated internal energy market in which energy can flow freely across its regions. Robust transmission and distribution infrastructure, as well as a well-interconnected European network are seen as key constituents for a successful integration of renewable energy [3]. To be more specific, spatial levelling effects of fluctuating renewable energy resources, such as on- and offshore wind as well as solar, make grid reinforcements attractive [4]. With that in mind, recent developments, such as the aforementioned rise in variability and uncertainty, make efficient solutions of long-term TEP problems even more relevant, but at the same time increase their complexity.

1.2. Model complexity and computational challenges

In order to keep long-term TEP models tractable for a large geographical scope and a high level of spatial and temporal detail, a common approach is to use load duration curves or other generic scenario reduction approaches, such as sampling and clustering methods on the model's input data [5], [6], and [7]. For instance, a reduction approach focused on the model's output data rather than the input data is shown in [8]. Computationally, condensing the input data yields a smaller number of variables and constraints in the resulting optimization problems and leads to more acceptable solution times.

Dimension reduction can be crucial when dealing with large-scale planning models, as they often cover a multi-regional and multi-national scope. Given the broad geographical extent, location-specific climate- and weather-dependent characteristics cannot be omitted, as temperature, wind speeds and solar irradiation exhibit significant variations within the considered scope. Hence, it is of great importance to sustain the characteristic correlations when approximating full year time series with reduced-size, sampled time series. This is particularly valid for TEP, as the incentives for grid investments are triggered by spatial differentials, e.g. a high non-dispatchable production in one area with low demand could use a transmission line to transmit power to another area with high demand and low non-dispatchable generation.

1.3. Literature review

Regarding different dimension reduction approaches, a comprehensive and consistent comparison including a variety of sampling as well as clustering techniques is still not available from the literature. In [9], a number of partitioning and hierarchical clustering approaches are compared for probabilistic load modelling. Recently, a comparison of different approaches for selecting representative days in generation expansion planning problems as well as a new optimization-based approach is presented in [10]. Other works such as [11] present a comparison of different clustering techniques in the context of power system reliability assessments.

What is not yet clear is the impact of different dimension reduction methods on the results of TEP problems, such as the model for offshore grid expansion shown in this study. Metrics describing the quality of a raw data sample might significantly deviate from the effect it eventually has on the TEP model's quality of results which needs to be addressed. Therefore, it is the key objective of this study to assess the impact of different sampling and clustering techniques reducing the number of hourly time steps being considered by a long-term TEP model on its performance and the quality of its results.

In the remaining part of this article, Section 2 discusses the methodology used to carry out the comparative analysis of dimension reduction techniques and their consequences for a long-term TEP model. Section 3 provides an overview of the employed dimension reduction techniques in this study, i.e. sampling and clustering methods, and elaborates on the two scaling options applied in this article. Introducing the second phase of the study, Section 4 highlights the mathematical formulation of the long-term TEP model and the analysed case study reflecting an offshore grid expansion in the North Sea area. The first part of Section 5 presents the sampling results, and the second part exhibits the long-term TEP model results capturing the model-dependent effects of the dimension reduction techniques. In Section 6, the obtained comparison and evaluation results are discussed, and Section 7 concludes the study.

2. Methodology

The study was conducted in two phases. In the first phase, a comparative study of dimension reduction methods was performed. To this end, selected sampling and clustering techniques are introduced. These techniques are then used to sample from the full year time series data of a reference data set, which includes load, on- and offshore wind, solar, and hydro availability data. By using a variety of sample sizes and two different scaling options, the sampled time series data is compared against the reference data set to assess the techniques' respective impacts on the time series data with a reduced dimension.

In the second phase of the analysis, the sampled data of the first phase is used as input for a long-term TEP model. For this purpose, a deterministic TEP model is formulated and solved by mixed-integer linear programming (MILP). It co-optimizes investment decisions and market operation in a power system consisting of several market areas, Norway (NO), Great Britain (GB), Denmark (DK), Belgium (BE), Germany (DE), and the Netherlands (NL). Beyond that, the model is capable of optimizing combined HVAC and HVDC grids, with the latter being able to adopt both radial- and meshed structures. In terms of power electronics, meshed (multi-terminal HVDC) structures are the most advanced solution, but according to previous research also the most cost-effective alternative from a socio-economic point of view, see [12], for instance.

The case study reflects an offshore grid in the North Sea area with a scenario horizon of 2030 showing high shares of non-dispatchable power production capacity, predominantly solar and wind. It is based on the 'Vision 4' which was developed as one of the four contrasting visions for the long-term horizon 2030 by the European Network of Transmission System Operators for Electricity (ENTSO-E). These visions differ in terms of energy governance and ambitions towards the ongoing deployment of renewable energy sources [13].

3. Dimension reduction techniques

Given the main purpose of deriving a reduced representation of the time-dependent full year input data set, different sampling and clustering techniques are presented in this section. Clustering techniques divide a given set of data points into groups or clusters with the intention of having the data points belonging to one group to be more similar to each other than to the data points outside of the cluster. The full data set, that this section refers to, consists of a data matrix containing all relevant time series categories (e.g. hourly electricity load, wind power or solar feed-in in each market area) as columns, while the rows represent observations (hourly values of a full consecutive year).

It has to be stressed that the following comparative analysis is based on the premise that inter-temporal constraints, e.g. storage continuity equations of hydro reservoirs, are not explicitly considered in the second phase. This allows for an easier sampling of the input data since the chronological order of occurrence can be omitted. Given the method-oriented nature of this study, this approximation is considered to be reasonable. For a different approach incorporating transitions from one hourly system state to the other through the year, see [14].

When dealing with multivariate time series analysis, it is important to recognize the need for preparing the time series data in an adequate way. Because the relationship between all time-dependent data points plays a vital role in the sampling phase, the necessary first step of scaling or normalizing the input data needs to be addressed. Depending on the focus of the model, there exist different ways of preparing the time series data for the sampling and clustering process, as also described in [7]. Hence, the following two scaling options have been included in the analysis:

1. *Technology-specific scaling* by the highest occurring value across all market areas for load, onshore wind, offshore wind, solar, and hydro, respectively.
2. *Scaling by the highest occurring value* across all market areas in the full data set (peak-load in market area DE).

Scaling option 1 ensures that the maximum value of each technology type, e.g. wind offshore, is scaled to 1 across all market areas. As a result, the variability of each technology type is evenly weighed in the data set which is sampled from. By contrast, scaling option 2 yields a better representation of the aggregated power system, as it attributes its weighing according to the highest power consumption or generation values, albeit at the cost of e.g. a small country's representation exhibiting lower installed capacities.

Moreover, a heuristic based on a moving average is included as a further variant in the analysis. It is motivated by the fact that the clustering methods show a tendency to not capture the outliers so well, which is why an additional step was added to the sampling process. For each time series profile and all sampled points or clusters, data point values belonging to this sub-sample or cluster are compared to the moving average (6 h window) of the full year time series profile. If more than 95 % of these data point values are below or above the sampled or cluster value, the lowest or highest value within this sub-sample or cluster is chosen as the new sampled point or cluster center, respectively.

3.1. Systematic sampling

In comparison with the subsequent techniques, the systematic sampling is a simple approach. Hence, it can be regarded as a rather straight-forward but efficient method of producing the required samples. With this technique, elements are selected from an ordered sampling frame assuming that each element in the full data set has the same probability of being chosen (equiprobability). It starts by choosing an initial element from the time series data set and then selecting every k^{th} element, where the sampling interval k is determined by the desired sample size and the number of observations (8760 h of a full year in this case). As a minor improvement, the initial element, and its thereby determined sample, is not selected at random but rather phase shifted to the next second k^{th} element amounting to a set of k resulting samples. Out of these, the one showing the smallest average normalized root-mean-square error (NRMSE) of the full year reference is chosen as the final sample.

3.2. k-means clustering

The k-means clustering approach is a common technique using the k-means algorithm [15] (or Lloyd's algorithm [16]). It is an iterative, data-partitioning algorithm assigning n observations to exactly one of k clusters defined by centroids. Through this process, subsets of the full data set are created and the centroid of each subset corresponds to the mean of all measurements belonging to it. The sample size k needs to be chosen before the algorithm starts. In [6], k-means clustering is used for determining system states of wind and load data in a power system with high renewable penetration, for instance.

3.3. k-medoids clustering

The k-medoids clustering technique is similar to k-means as both partitioning methods try to divide a set of measurements or observations into k subsets so that the subsets minimize the sum of distances between a measurement and a center of the measurement's cluster. How the center or cluster of the subset is determined is the key difference between the k-means and k-medoids method. In the k-medoid algorithm, the center of the subset is an actual member of the data subset, called a medoid.

3.4. Hierarchical clustering

As a further dimension reduction method, the agglomerative form of hierarchical clustering analysis is used in this study. At each step, its underlying stepwise algorithm merges two objects, the ones with the least dissimilarity, thereby clustering the objects of the original data set. There are different ways of how the dissimilarities between clusters of objects or the linkage can be defined. Here, Ward's linkage [17] is used resulting in clusters with minimum inner squared distances (minimum variance algorithm). Hierarchical clustering with Ward's algorithm has been used in [7], for example, for the purpose of grouping similar days of full year data to decrease the dimension of a long-term power system model.

3.5. Moment-matching

In this context, the moment-matching technique refers to the approach presented in [18]. It belongs to a group of approaches aiming to minimize the selection of samples with respect to a predetermined criterion (external validity indices) [10]. This sampling algorithm selects a sample of hours from the full data set that minimizes the sum of square deviations of the moments between sampled hours and the full year time series data. The moments represent statistical measures such as correlation, mean and standard deviation. First, candidate samples are created by drawing 10,000 random samples from the full year data set. In order to then find appropriate estimators for the original time series data, the sample with the smallest squared moment deviation is chosen from the candidate samples. For instance, this technique has been successfully used for expansion planning with multivariate time series in [19].

4. Long-term TEP Model

This section gives a brief introduction to the long-term TEP model used in the second phase of the comparative analysis of dimension reduction techniques in this article. For more background information, see e.g. [20], [21], and [22] serving as a foundation for the following model (PowerGIM).

In order to incorporate uncertainty, the model is formulated as a two-stage stochastic program which relates to a mixed-integer linear program (MILP) in its extensive form. Integer variables are used to decide upon transmission infrastructure investments in the first stage, while the second stage problem is a pure linear program (LP) reflecting generator capacity investment and market operation. By only considering one scenario, the model is equivalent to a deterministic program. A compact model formulation of the stochastic MILP is given in (1) below.

$$TC = \min_x c^T x + E_\xi[\min_{y(\omega)} q(\omega)^T y(\omega)] \tag{1a}$$

s.t.

$$Ax \leq b \tag{1b}$$

$$T(\omega)x + Wy(\omega) \leq h(\omega), \quad \forall \omega \in \Omega \tag{1c}$$

$$x = (x_1, x_2) \geq 0, x_1 \in \{0, 1\}, x_2 \in \mathbb{Z}^+, y(\omega) = (y_1(\omega), y_2(\omega)) \geq 0, \quad \forall \omega \in \Omega$$

In (1a), the objective function is divided into two stages; first the costs related to infrastructure investments, and second, the expected costs of market operation, $y_1(\omega)$, and generator capacity investments, $y_2(\omega)$, dependent on a discrete set of scenarios, Ω. For the work presented in this paper, generator capacity investments are disregarded in order to narrow down the scope to grid investments.

The vectors and matrices c, b, and A are associated with the first stage variables, i.e. investment in grid infrastructure. c is the cost vector for both fixed and variable node- and branch costs. b restricts the investment decisions, e.g. by the maximum allowed capacity per investment block (e.g. 1000 MW per branch), and A is the corresponding coefficient matrix to those investment constraints.

The second stage parameters are dependent on the realization of $\omega \in \Omega$, i.e. the parameters are not quantified before uncertainty is revealed. $q(\omega)$ is a cost vector for the marginal cost of generation and the capital capacity costs for generation. $h(\omega)$ is the right-hand-side restrictions for scenario ω, i.e. relevant restrictions on market dispatch and investments in generator capacity. $T(\omega)$ is the so-called *transition matrix* associated with first stage investments and it contains scenario and/or time-dependent data affecting operation in the second stage. The recourse matrix, W, is considered fixed in this model since as the coefficients in the matrix are independent of the realization of ω.

As stated earlier, only one scenario represented by ENTSO-E's Vision 4 is considered in the context of this study, that is the resulting model yields the same results as a deterministic program. Moreover, investment decisions are static implying that these are only made for one time step. Note that construction delays of investments are not considered. The economic lifetime of investments is assumed to be 30 years and the discount rate is 5 %. A CO_2 price amounting to 30 €/tCO_2 is used in order to reflect the social marginal cost of emissions from power plants based on fossil fuel, such as oil, gas, and coal.

5. Results

5.1. Sampling and clustering

The effect of using the two different scaling options is illustrated in Fig. 1. Because the load in market area DE contains the highest occurring value across all market areas, scaling option 2 results in a closer fit of the reference load profile than scaling option 1. By contrast, it can be seen that scaling option 1 produces a better match for the offshore wind profile. These observations correspond with the scaling methodology presented in Section 3.

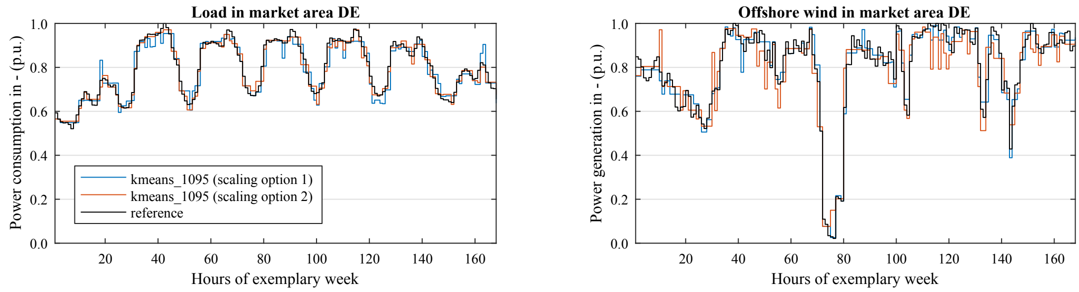

Fig. 1. Comparison of k-means clustering with two scaling options versus reference for load and offshore wind time series data in market area DE

The load level is the underlying driver for the resulting operational costs calculated by the TEP model. Fig. 2 provides useful information about the relative load levels resulting from the different sampling and clustering techniques.

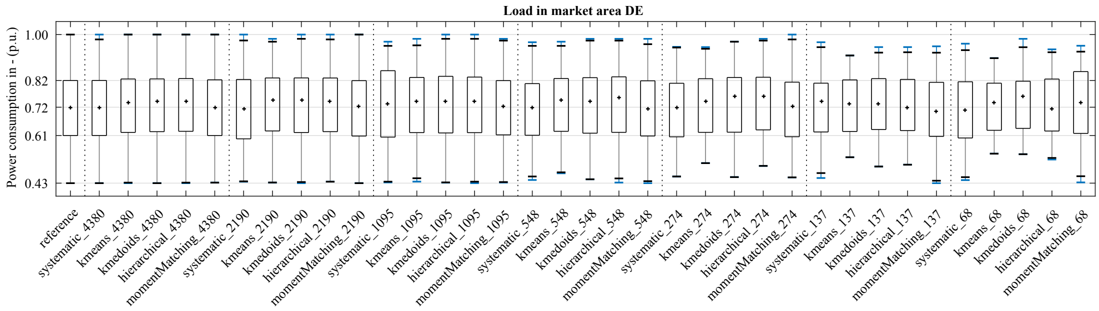

Fig. 2. Quartiles of reference and sampled data distributions for the load in market area DE (scaling option 1, effects of heuristic shown in blue)

For almost all techniques, the box plots suggest that the average load levels tend to be higher than in the reference case, although the highest values are not captured anymore. One exception, however, are the samples generated by the moment-matching method. Another important insight is that the heuristic introduced in Section 3 can partly capture the most extreme values of the original data. That said, the heuristic works better for the bigger sample sizes since it becomes harder to fulfill the 95 % criterion. In general, it must be noted that the heuristic comes at a cost, particularly for the clustering techniques, as its result deviates from the techniques' output (Fig. 3).

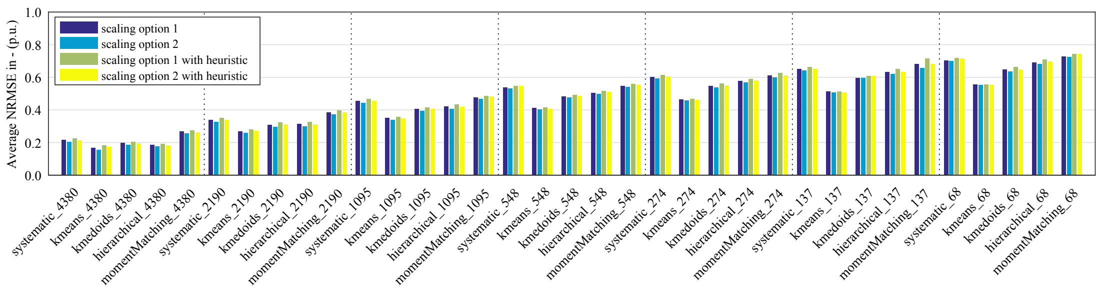

Fig. 3. Average normalized root-mean-square error (NRMSE) calculated over all time series categories for each technique and sample size

In order to quantify the overall fit in terms of profile deviations from the reference case, the NRMSE is calculated as an average for all time series, i.e. load, onshore wind, offshore wind, solar, and hydro, for each technique and sample size, as shown in Fig. 3. The NRMSE measure suggests that the *k*-means clustering performs best for all sample sizes, particularly with scaling option 2 without the heuristic algorithm (light blue bars). To put it another way, it stands to reason that *k*-means also yields the most accurate long-term TEP model results, which will be further assessed in the next section.

5.2. Long-term TEP case study

Based on the sampling and clustering results of Subsection 5.1, Table 1 gives an overview of the resulting key metrics of the long-term TEP case study simulations. As expected, with decreasing sample size the average solution

Table 1. Average solution time reduction and average cost accuracy for each technique with respect to the full year reference case.

	Average reduction in solution time per sample size Solution time as share of full year reference in %							Average cost accuracy Deviation of full year reference in %		
	4380	2190	1095	548	274	137	68	Total (objective)	Investment	Operation
Systematic	17.83	5.69	2.11	1.03	0.36	0.17	0.09	1.48	0.90	1.51
k-means	23.11	5.75	2.14	0.86	0.62	0.21	0.11	-1.46	-3.36	-1.34
k-medoids	21.23	6.94	2.26	1.05	0.46	0.25	0.09	0.70	-1.63	0.84
Hierarchical	20.52	6.74	2.33	1.16	0.44	0.16	0.09	0.67	-0.23	0.72
Moment-matching	23.47	5.67	2.40	0.83	0.40	0.20	0.10	1.35	2.32	1.29
Reference (abs.)	2016.1 s							473.1 bn€	26.9 bn€	446.1 bn€

time can be significantly reduced. To distinguish between pure market and investment decision effects, the total costs defined in the objective function (1a) are broken down into both operational and investment costs. Note that the share of operational costs is significantly higher than that of the investment cost. Keeping in mind that the *k*-means clustering performed best among the sampling and clustering results, it becomes clear that this is, on average, not the case for the model-dependent results reported in Table 1. In fact, it exhibits a poor performance regarding the average deviation in investment strategy and performs only slightly better than the systematic sampling when considering total cost deviations. The hierarchical clustering shows the highest average cost accuracy, followed by *k*-medoids.

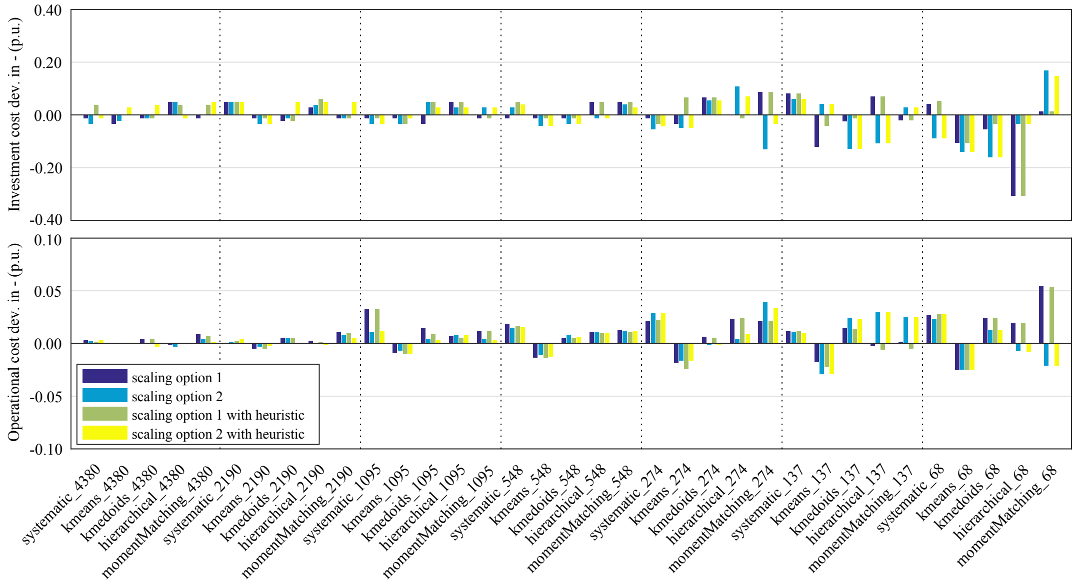

Fig. 4. Comparison of relative investment and operational cost deviations or each technique and sample size (sampled - reference)

5.2.1. Investment and operational costs

In Fig. 4, a more detailed breakdown of the relative investment and operational cost deviations is presented. Several results can be taken from this figure: First, for all methods, both investment and operational cost deviations generally increase with a reduced sample size. Second, while the other methods rather overestimate the operational costs, *k*-means shows a consistent underestimation confirming the observation above. Third, the scaling options do seem to have a bigger impact on the deviations than applying the heuristic. More specifically, hierarchical clustering seems to work slightly better with scaling option 1, while particularly for *k*-medoids, systematic sampling, and moment-matching, scaling option 2 presents a better combination. However, there is no clear indication as to which scaling option performs better.

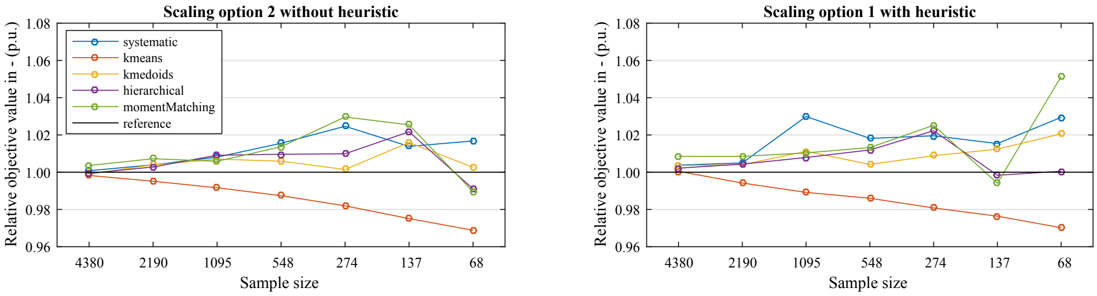

Fig. 5. Convergence of the relative objective value for each sample size and method, scaling option 2 without heuristic (left) and scaling option 1 with heuristic (right)

As can be seen from Fig. 5, the convergence results of the relative objective are in line with the previous findings. For the half year sample size (4380 h), all techniques show relative values close to 1. At the opposite end, the moment-matching technique displays a deviating behavior for the 68 h sample size. Interestingly, hierarchical clustering achieves relatively low deviations for the smallest sample size with scaling option 1 and the applied heuristic.

5.2.2. DC cable investments

In Fig. 6, the resulting differences in investment strategy are presented as deviations in DC cable investments.

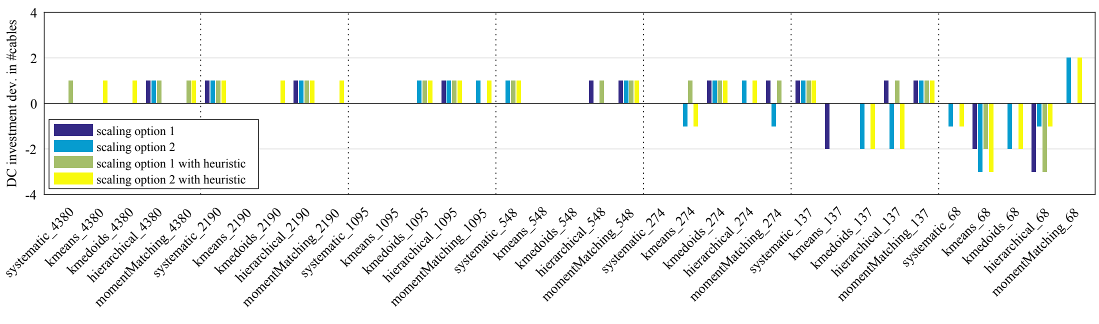

Fig. 6. Comparison of DC cable investment deviations or each technique and sample size (sampled - reference)

Out of the 14 DC cable investments in the full year reference, this finding implies that over-investments are limited to one DC cable, except for the moment-matching technique with the smallest sample size. Under-investments do not occur for sample sizes bigger than 274 h, while they can amount to three DC cables for the smaller sample sizes. Hence, there is reason to believe that the high load levels indicated in Fig. 2 might be the explanatory driver for the occurring over-investments. This is because the additional transmission capacity is used to cover the loads more efficiently with cheap generation technologies located elsewhere.

6. Discussion

There are a few assumptions and limitations to be kept in mind when discussing the results obtained in the comparisons above. As stated earlier, short- to long-term inter-temporal constraints (e.g. seasonal hydro reservoir continuity) are not accounted for in the TEP model. At the same time, however, this assumption facilitates the sampling and clustering of individual hours because the chronology of the original time series data can be ignored. Further, the number of considered market areas and technologies, and thus the number of time series corresponds to a full-size problem. The effect of increasing the time series quantity of the original data set, e.g. from a two time series test case, has not been investigated. This fact should not be neglected, however, since a larger dimensionality of the original data set requires more observations to obtain reasonable sampling and clustering results.

The analysis suggests that the dimension reduction techniques may score very well in terms of capturing distributions or error measures such as the presented NRMSE, but that the output from the TEP model employing the samples gives deviating score patterns in terms of investment and operational costs of a potential future offshore grid. This insight becomes particularly obvious for the *k*-means clustering approach, which is performing well in Subsection 5.1 but consistently underestimating the total costs in the TEP model runs in Subsection 5.2. Comparing it with *k*-medoids, the way of determining the centroids seems to play an important role. The agglomerative hierarchical and *k*-medoids clustering show comparatively good results when quantifying both the NRMSE and the effects on offshore grid expansion decisions in the North Sea case study.

It has been shown that the scaling options have a greater impact than the applied heuristic. Then again, no clear indication can be given as to the more suitable choice of either one of the two scaling options. Hence, paying careful attention to different scaling options for the original data set seems appropriate.

7. Conclusion

Motivated by the concern of growing model complexity and increasing computational challenges, this article investigates the impact of dimension reduction methods for power system models. To this end, a selection of dimension reduction techniques is analysed and used to sample from hourly full year time series data including load and renewable generation.

The main contributions include a comprehensive comparison of sampling and clustering techniques with different scaling options which were used in combination with a large-scale TEP model for a North Sea offshore grid case study. Further, a high number of market areas and technology options, i.e. large number of time series categories, was considered in this study. It can be concluded that techniques performing well in the sampling and clustering process do not necessarily produce reliable results in the large-scale TEP model.

A subsequent analysis of dimension reduction techniques and their application in long-term power system models can include the use of more sophisticated heuristics, particularly in investment models as they significantly depend on the highest occurring values in the original data sets. Future work should include ways of incorporating inter-temporal constraints to better capture medium-term dynamics and the operational flexibility in power system models. For instance, this could be done by employing dimension reduction approaches, e.g. [14], or developing alternative solution strategies involving decomposition for the full year problem.

Acknowledgements

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The long-term TEP model used in this article, PowerGIM, is an open-source model available at Bitbucket. The authors would like to thank Gurobi for a powerful optimization solver.

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Paper B

Kristiansen, M., Korpås, M., and Härtel, P. (2017). Sensitivity analysis of sampling and clustering techniques in expansion planning models. In *2017 IEEE International Conference on Environment and Electrical Engineering and 2017 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I CPS Europe).*

Paper C

Kristiansen, M., Korpås, M., Farahmand, H., Graabak, I., and Härtel, P. (2016). Introducing system flexibility to a multinational transmission expansion planning model. *19th Power Systems Computation Conference (PSCC'16).*

Paper D

Kristiansen, M., Korpås, M., and Farahmand, H. (2018b). Towards a fully integrated North Sea offshore grid: An engineering-economic assessment of a power link island. *Wiley Interdisciplinary Reviews: Energy and Environment*.

Towards a fully integrated North Sea Offshore Grid: An engineering-economic assessment of a Power Link Island

Martin Kristiansen, Magnus Korpås and Hossein Farahmand *

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Article Type:

Focus Article

Abstract

An increasing share of variable power feed-in is expected the next decades in the European power system, with a particularly high offshore wind potential in the North Sea region. This demands more temporal- and spatial flexibility in the system, and an adequate grid infrastructure can provide both. This article presents an engineering-economic approach evaluating the impact of novel infrastructure designs towards a fully integrated North Sea Offshore Grid (NSOG), including TenneT's vision of a Power Link Island (PLI). A PLI is an artificial island for transnational power exchange and distribution of offshore wind resources. We introduce the concept and evaluate the economic benefits and system implications under three different case studies incorporating 2030 scenarios from ENTSO-E. The results demonstrate system cost savings up to 15.8% when comparing a fully integrated PLI solution with traditional, radial typologies. The PLI did in general result in more efficient system dispatch of wind resources, where the involvement from Norway, Great Britain, and Germany occurred most frequently in terms of grid reinforcements and expansions.

*Department of Electric Power Engineering, Norwegian Uni. of Science and Technology (NTNU), Norway.

A NORTH SEA OFFSHORE GRID

The North Sea Offshore Grid (NSOG) has been identified as one of the strategic infrastructure projects in EU Regulation No 347/2013 with the twofold purpose of integrating offshore wind resources and integrating markets for increased cross-border trade (EU Commission, 2011; European Commission, 2016). Multiple studies have addressed the added value of a NSOG in terms of cost-efficient utilization of variables renewable energy sources (VRES), reduced greenhouse gas (GHG) emissions, and increased security of supply (Van Hulle et al., 2009; Egerer, Kunz, & Hirschhausen, 2013; Gorenstein Dedecca & Hakvoort, 2016). In order to speed up investments and attract private investors, financial support netting €5.35bn is provided by Connecting Europe Facility (CEF), but this is only a small portion of the estimated €140bn worth of necessary electricity infrastructure upgrades the coming decade (ENTSO-E, 2016).

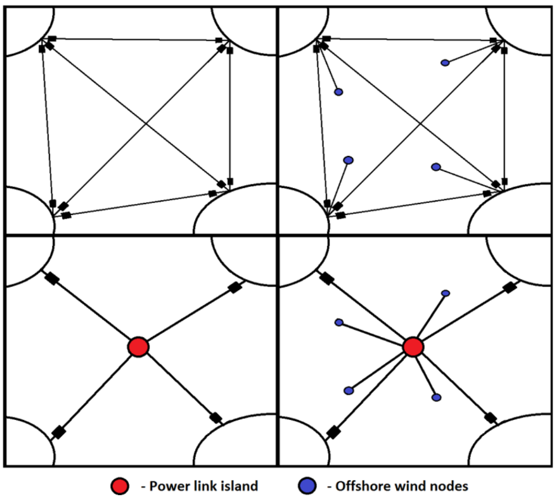

Figure 1: Illustration of different levels of grid integration ranging from radial solutions (in the two upper brackets) to integrated, or meshed, solutions (in the two lower brackets). The solution depicted in the lower-right corner represents a full Power Link Island (PLI) integration. Source: (Solli, 2017).

Typologies, being a combination of grid topology and technology, are traditionally divided into two groups; radial and integrated (Trötscher & Korpås, 2011; Gorenstein Dedecca & Hakvoort, 2016) as shown in Figure 1. A radial typology comprise point-to-point high voltage direct current (HVDC) connections, while an integrated typology[1] enables multiple HVDC connections at one joint – yielding a modular and flexible option with potential benefits in capital- and operational costs. For instance, in order to connect four countries one would need six transmission corridors in order to interlink them all with radial typology, in addition to individual offshore wind power (OWP) connections, while with an integrated typology the number of corridors is reduced from six to four (with approximately half the length, each). This is clearly illustrated with Figure 1. Additionally, an integrated typology will also achieve a higher level of utilization at each transmission corridor. The concept of a Power Link Island (PLI) is a large-scale augmentation of the latter integrated typology with significant potential in economies of scale (van der Meijden, 2016). According to its promoter, TenneT, a PLI can span an area of 6 km^2 and cost approximately €1.5bn for the artificial construction of the island itself; i.e. a pile of stones and sand in the shallow water of the Dogger Bank area (TenneT, 2017b).

A PLI has the capacity to connect 30 GW OWP capacity and by combining multiple PLIs into a so called offshore wind power hub the capacity can be expanded to 100 GW, which translates into enough energy supply for 70-100 million consumers in Europe (TenneT, 2017a). This can potentially serve a major contribution in reaching the European 2050 climate targets (EU Commission, 2011) where approximately 230 GW OWP capacity is needed, whereas 180 GW in the NSOG area (TenneT, 2017a). It is claimed that such an island can be scheduled for operation by approximately 2035 (TenneT, 2017b), connecting Norway (NO), Denmark (DK), Germany (DE), The Netherlands (NL), Belgium (BE), and Great Britain (GB).

Nevertheless, in addition to being an important milestone for OWP integration and cross-border power exchange, a PLI does also possess an advantage of large surface areas in close connection with existing European gas infrastructures. That is, in cases of energy surplus or electricity grid congestion there is a considerable potential in Power-to-Gas (PtG) production at the island (TenneT, 2017a). For instance, hydrogen production for energy storage,

[1]Integrated typologies are often referred to as meshed grids.

heating- or mobility sector. This would impose a stronger coupling of the aforementioned sectors, consequently leading to more flexibility options (Kondziella & Bruckner, 2016) and complex system interdependencies that could affect the benefits of grid expansion (Jesse Jenkins & Nestor Sepulveda, 2017). The gas could also be used as storage and converted back into electricity, but with a round-trip efficiency spanning 35-50% it is currently not profitable with today's electricity price variations and electrolysis technology (Lund, Lindgren, Mikkola, & Salpakari, 2015).

As a response to recent discussions about such an island, this article presents an engineering-economic analysis of a PLI in the NSOG using data for year 2030 (ENTSO-E, 2016). Our scope is to assess its performance under varying degrees of offshore wind development, in addition to national re-allocations from onshore variable renewable energy source (VRES) to offshore wind capacity. The contribution is twofold; i) help establishing a foundation for future research on this relatively new topic, and ii), approximate the added value of a fully integrated PLI solution using an optimization program for power system expansion planning.

METHODOLOGY

Results are obtained by designing a set of case studies that are analyzed using an expansion planning model. The model is well documented in, e.g., (Kristiansen, Munoz, Oren, & Korpås, 2017) and (Kristiansen, Korpås, & Svendsen, 2018), so readers that are interested in the model formulation is referred to those. The following subsections discuss our approach for this paper in greater detail.

An expansion planning model

We use an optimization program for transmission expansion planning, called PowerGIM (Kristiansen et al., 2018), in order to co-optimize investment decisions and market operation for the considered case studies over an economic lifetime of 30 years starting in year 2030. The model is formulated as a mixed-integer linear program (MILP) and incorporates variability in wind, solar, hydro and load by sampling multiple, hourly time steps from full-year profiles (Härtel, Kristiansen, & Korpås, 2017; Kristiansen, Härtel, & Korpås, 2017). Consequently,

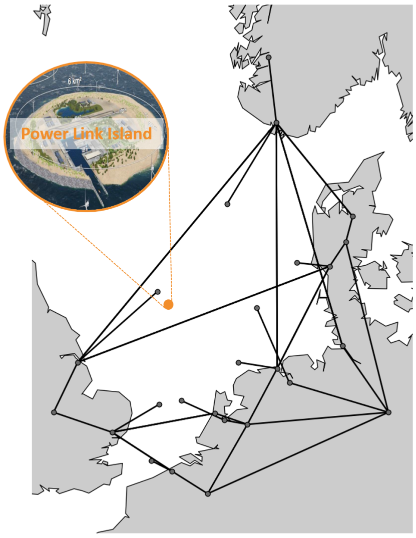

Figure 2: Illustration of the base case grid infrastructure used in the model. The orange dot represent the expected location for a power link island.

this sampling approach ensures that different power flow patterns are accounted for since time series are generated for unique geographical coordinates from numerical weather data (COSMO-EU) (Graabak, Svendsen, & Korpås, 2016).

In turn, this means that the model implicitly incorporates the value any geographical smoothing effects and flexibility needs that arise from the spatial- and temporal mix of variable supply (wind and solar) and demand (Hasche, 2010). This is also one of the objectives with a NSOG, and in particular a PLI, which is within the scope of the following case study spanning six countries; Norway (NO), Denmark (DK), Germany (DE), The Netherlands (NL), Belgium (BE), and Great Britain (GB) as illustrated with the base case model setup in Figure 2. The orange coloured dot in the figure depicts the potential location for a PLI.

Grid expansion is known to yield considerable, material price impact in adjacent price areas (Hogan, 2011), consequently affecting the market landscape in which generators operates their units and plans long-term capacity expansion (Alayo, Rider, & Contreras, 2017) [2]. Repercussions might also arise in surrounding, third-party areas which are not directly

[2]Market landscape as in electricity prices and optimal portfolio of generation technologies. For instance,

connected (Kristiansen, Munoz, et al., 2017) with the transmission projects. Hence, the geographical span of the case study depicted in Figure 2 represents some limitations as the interdependencies with surrounding countries might impact the resulting benefits of a PLI. For instance, France might provide or demand flexibility enabled by a fully integrated PLI through, e.g., Belgium's domestic grid.

Cost assumptions

The construction costs for the PLI itself is estimated to be around €1.5bn. This is for stones and sand, only, so any additional costs for equipment will add on top of this. In comparison with traditional platform costs one would benefit from a PLI in terms of economies of scale, i.e. by utilizing a larger area for modular constructions, storage of personnel and spare parts, in addition to subsequent benefits in term of operation and maintenance. In this study, traditional platform costs amounts to €50m for AC and €406m for DC[3], which is assumed to be large enough for a 2000 MW VSC[4]. This means that a PLI could serve approximately 15 times the capacity of a traditional platform. For an excellent review on costs for offshore high voltage transmission lines and power electronics, please consult (Härtel, Vrana, et al., 2017).

Hence, the expansion planning model can choose to invest in a traditional platform or a PLI, with its associated costs. If a PLI is chosen, all transmission lines connected to it needs one converter, each. The same is the case for an offshore platform, but its size is limited to siting a maximum capacity of 2 GW (compared to 30 GW for the PLI). Operation- and maintenance costs are not included in the study. As a result, total investment costs associated with a PLI are likely to be over-estimated as its economies of scales are not fully captured (compared with traditional platforms).

if wind capacity is imported through new transmission capacity this would lead to lower prices and the need for flexibility in order to balance supply-demand (Cochran et al., 2014).

[3] AC and DC stands for alternating current and direct current, respectively. The latter is a preferred option for transmitting power over long distances, and particularly when using submarine cables.

[4] Voltage Source Converter (VSC) is a rather immature technology, but also the most prominent one for integrated/meshed HVDC grid typologies (Trötscher & Korpås, 2011).

	Supply [GW]	VRES [%]	OWP [GW]	Peak demand [GW]
Vision 1	420	48.8	89	209
Vision 4	523	56.5	154	204

Table 1: Summary of aggregate supply- and demand mix, including the share of Variable Renewable Energy Sources (VRES) and Offshore Wind Power (OWP). VRES comprise wind, offshore wind, solar PV and "other RES" according to definitions by (ENTSO-E, 2016).

Case study setup

There are nine scenarios in total (Scenario A - I), branching from three groups of case studies. The first one is a study of varying degrees of PLI integration into the NSOG. The second group studies the impact of re-allocating onshore VRES capacity into OWP capacity at offshore coordinates, utilizing the offshore wind resources and grid infrastructure. Finally, in the third group of scenarios we try to see how the system handles additional OWP capacity on top of the input data given by ENTSO-E, by placing this capacity at different locations in the system. All three clusters of case studies are ran with two sets of input data from the TYNDP 2016[5] (ENTSO-E, 2016), comprising Vision 1 ("slow progress") and Vision 4 ("green revolution"). A summary of aggregate supply- and demand is given in Table 1, while a more detailed illustration for Vision 4 is found in the Appendix including fuel costs and CO_2 price (Table 2).

Varying degree of Power Link Island integration

Different degrees of PLI integration are assessed ranging from radial grid typology to a fully integrated PLI with candidate branches to offshore wind nodes and national onshore nodes. The scenarios are described as follows:

(A) Radial grid expansion.

(B) PLI expansion with 30 GW OWP from GB and candidate branches to be expanded in connection with surrounding countries.

[5]Ten-year network development plan (TYNDP).

(C) Scenario B + candidate branches to surrounding offshore wind nodes.

Offshore versus onshore VRES generation capacity

The possibility for a fully integrated typology in Scenario C is used for the following case studies. Here, a certain share of onshore VRES capacity is re-allocated from being onshore to offshore. This share is calculated with respect to the sum of national solar PV and onshore wind. First, 10% is moved from onshore to offshore, followed by an increase to 25% and 50%. Note that all the re-allocated capacities are converted into OWP utilizing its strong feed-in profiles at respective offshore coordinates. Hence, the amount of energy feed-in to the system is likely to increase although aggregate supply capacity maintains the same.

(D) Scenario C + 10% onshore VRES allocated to national offshore nodes.

(E) Scenario C + 25% onshore VRES allocated to national offshore nodes.

(F) Scenario C + 50% onshore VRES allocated to national offshore nodes.

Additional offshore wind power capacity on top of initial input data

This case study comprise three scenarios studying the impact of different geographical allocations of additional 30 GW OWP capacity. In this case, both aggregate supply capacity and energy feed-in will increase.

(G) Scenario C + 30 GW OWP distributed to all countries' offshore nodes relative to their initial share with respect to total OWP system capacity.

(H) Scenario C + 30 GW OWP directly to the largest OWP node in the system, which belongs to GB (Dogger bank) close to the PLI.

(I) Scenario C + 30 GW OWP directly to the island.

It should be noted that the scenarios are not meant for consistent comparisons due to variations in available capacity and energy. The focus is rather to assess the implications and robustness of offshore grid designs, and particularly to see whether the expansion planning model finds a PLI beneficial for a majority of the scenarios.

Limitations

Although this article presents a real case study, there are some limitations that should be noted. For instance, there are no boundaries for new transmission capacity and some transmission corridor expansions might therefore be very unrealistic. For instance, public opposition will most certainly make it difficult to build, say, 15 transmission lines/cables in parallel. Moreover, the market operation in which grid investments recover their costs does not account for unit commitment constraints such as start-stop, ramping, and minimum up- and downtime. This would somewhat over-estimate the flexibility of, e.g., nuclear and coal units and possibly lead to under-investments in grid expansion.

RESULTS

Recall that the investment costs for an offshore island is €1.5bn. That is, the cost for a PLI as an alternative to traditional platforms. Costs for power electronics at the island are indirectly accounted for with new cables being built, meaning that the total costs for transformers and power electronics most likely will be over-estimated as the model will invest in more equipment than necessary. This means that we only account for economies of scale for the island itself, and not for equipment nor any benefits related to operation maintenance of the OWP capacity near the island. For more information regarding cost calculations of transmission projects, please consult (Svendsen, 2013) for the approach and (Härtel, Vrana, et al., 2017) for an updated review on data.

Power Link Island yields significant cost savings

Figure 3 shows the resulting investment- and operational costs for all scenarios, both in a future system with low shares of VRES (Vision 1) and high shares of VRES (Vision 4). First point to notice is that operational costs are higher for Vision 1 than for Vision 4 due to significantly less low-cost supply capacity in Vision 1, such as wind and solar, compared with relatively similar peak demand levels (see 1). The yearly energy consumption is also relatively identical for both cases, amounting to 1300 TWh.

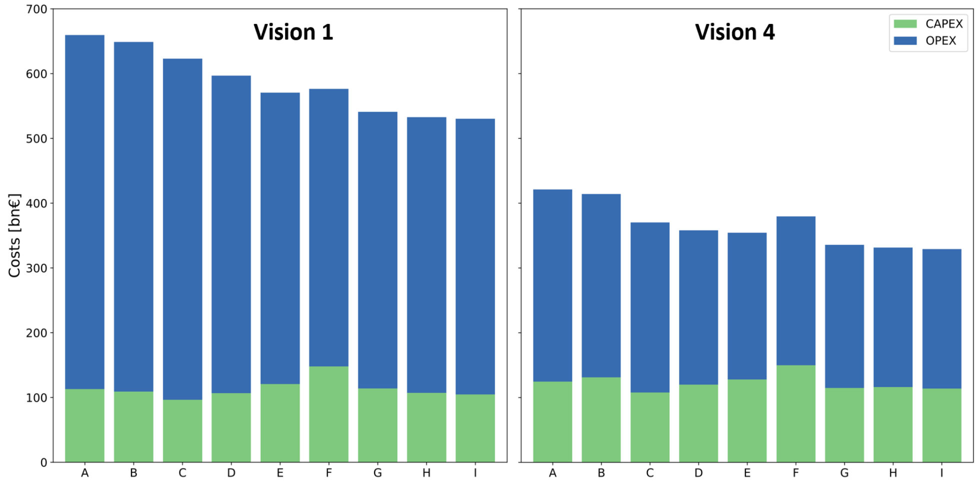

Figure 3: Investment- (green) and operational costs (blue) from the nine different case studies using data from ENTSO-E's least ambitious scenario Vision 1 (left part) and Vision 4 (right part) with high shares of VRES.

The investment costs are generally higher with Vision 4 due to a stronger need for flexibility, where a NSOG has proven to be a prominent solution (North Sea Grid, 2015). The latter is particularly evident for high VRES cases, such as Vision 4, in combination with Norwegian hydropower (Huertas-Hernando et al., 2017). Second, and most importantly, recall that the three first scenarios (A - C) represents different degrees of PLI integration, from no island to an fully integrated PLI serving as a hub for transnational power flow and for OWP distribution. Figure 3 demonstrates that the largest costs savings are found progressively for those three scenarios, whereas the consecutive scenarios builds further on Scenario C (fully integrated).

The total cost savings for a fully integrated PLI amounts to €36.8bn and €50.7bn in Vision 1 and 4, respectively. Parts of these savings are due to the transnational power exchange role of a PLI (Scenario B), but the largest portions of savings arise from the combination of being a transnational power hub and an OWP hub (from Scenario B to C). That is, a fully integrated PLI will require less investments, enable increased utilization of new transmission corridors, and be able to distribute OWP more efficiently to surrounding countries instead of re-routing through multiple countries (with consequently higher transmission losses due to longer distances). This is in line with previous NSOG studies claiming that the level of grid integration tends to relieve grid congestion (NSCOGI, 2012; Farahmand, Huertas-Hernando, Warland, Korpas, & Svendsen, 2011).

Key players for a Power Link Island

The aforementioned cost savings are a result of different system compositions, i.e. a combination of temporal- and spatial characteristics in supply and demand. We can therefore try to identify the most crucial contributors to system cost reductions.

Figure 4 illustrates, with a colour-scale plot of capacity expansion levels, that GB and NO were the two countries representing the largest share of total investments, both in terms of national grid reinforcements and HVDC connections with other countries and the PLI. There is a strong pattern of capacity investments between the two countries as well, due to high gas prices in GB relative to flexible hydropower in NO. Hence, the model found it cost-efficient to use Norwegian hydropower elsewhere in the system, and particularly in GB for Vision 1. The same expansion patterns were found for Vision 4, except that significantly higher levels of OWP (see Table 1) lead to slightly less investments between the two countries (NO and GB).

Stress testing for future VRES development

Since the future deployment of wind power capacity is uncertain, we demonstrate with Scenario D to F how a re-allocation from onshore to offshore VRES capacity affects investment decisions in grid expansion, as well as its subsequent impact on costs. In the latter three scenarios we basically move a share of VRES capacity from onshore to offshore facilities within domestic coordinates, ranging from 10-50% of onshore VRES (solar and wind).

Figure 3 shows an overall decrease in total costs for Scenario D to F, compared with Scenario C, which serves as a base case for this development. One exception is the 50% re-allocation of VRES in Vision 4 (Scenario F) where total costs are higher than for Scenario C. Hence, there is a certain threshold between 0-50% re-allocation for what is cost-efficient in

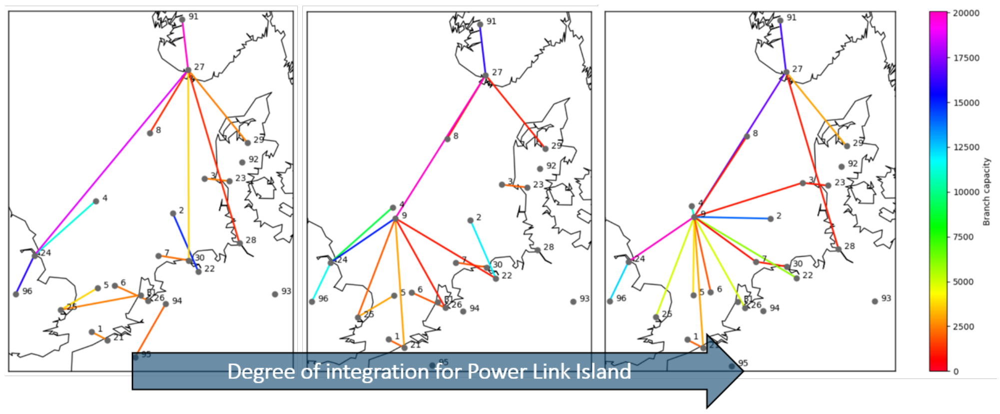

Figure 4: Grid expansions moving from Scenario A (left plot) to Scenario C (right plot), i.e. towards full integration of a PLI as a multinational hub for both cross-border exchange and offshore wind power distribution. Illustrations are based on Vision 1.

Vision 4. The underlying driver for this observation is that VRES represents a larger share of the total supply in Vision 4, where a 50% re-allocation away from the load centers requires considerable investments in cross-border and domestic grid infrastructure in order to avoid load shedding, which exceeds the potential margins to be gained in terms of operational flexibility, better wind resources and subsequent cost savings (which is not infinite as the lowest possible marginal cost (price) is close to 0 €/MWh). Moving VRES away from load centers throughout the system led to NO and DE being the two largest contributors in terms of grid expansion, compared with NO and GB in Scenario C.

As a step further in the stress test, additional 30 GW OWP capacity were added on top of the initial data input. This had minor, and close to uniform, impact on costs, geographical contribution to system benefits, and average area prices. The optimal grid typology remained about the same, independent on the geographical allocation of the additional 30 GW OWP capacity. This implies that the resulting typology in Scenario C, i.e. the fully integrated PLI, is flexible enough to handle this extra supply. However, an evident finding is that the most cost-efficient equilibrium arises when the 30 GWs are allocated directly in connection with the PLI - due to its distributional flexibility as stated earlier in this section.

DISCUSSION

One observed result is the considerable cost-savings of introducing a PLI. In fact, the model found it cost-efficient to invest in a PLI for all nine considered scenarios, and for both a low VRES (Vision 1) and high VRES (Vision 4) future. However, the benefits were in general higher for the most ambitious scenario (Vision 4) due to its temporal- and spatial mix of demand and supply benefiting from the hub functionality of a PLI; cross-border trade and offshore wind distribution. The same results were found in (NSCOGI, 2012) when comparing meshed typologies with radial ones, where the authors identified increasing benefits of an integrated NSOG with increasing shares of VRES. Similar findings have also been supported by, e.g., (Strbac, Moreno, Konstantelos, Pudjianto, & Aunedi, 2014) and more recently (Konstantelos et al., 2017).

Total cost savings for a fully integrated PLI were in the range of 12.6% (Vision 1) to 15.8% (Vision 4), compared with a radial typology (Scenario A). A re-allocation from onshore to offshore wind capacity had a positive impact on system costs, with diminishing returns up to the PLI's maximum capacity near 30 GW. It stands to reason that the latter is due to flexible hub functionality at the PLI, meaning that it has multiple options to distribute this OWP capacity without the need for grid expansion. Finally, by including additional offshore wind capacity on top of the two ENTSO-E visions, allocations in near connection to the PLI gave considerably higher cost-savings than allocating the same amount to national, offshore hubs (not connected to the island). Again, the flexible hub functionality might be a possible explanation in combination with over-supply of generation capacity (not enough demand to distribute it).

In light of previous studies (NSCOGI, 2012; Strbac et al., 2014; Konstantelos et al., 2017), it is clear that increasing levels of grid integration yields multiple benefits. The PLI can be viewed as the ultimate level of integration due to its relative high capacity. However, integrated grid solutions are challenging in terms of cooperation among bordering countries as discussed in, e.g., (Gorenstein Dedecca, Hakvoort, & Herder, 2017). One example being the distribution of costs and benefits, due to asymmetric implications of multinational projects. That is, some countries might gain more benefits than others, as illustrated in for the NSOG in (Egerer et al., 2013) and (Kristiansen, Munoz, et al., 2017).

CONCLUSION

This article performs case studies of TenneT's vision about a Power Link Island (PLI) in the North Sea Offshore Grid (NSOG) serving a twofold purpose as an hub for cross-border trade and offshore wind power (OWP) distribution. We use an optimization program for power system expansion planning to assess the added value of a PLI in the NSOG under the assumption of two distinct futures with low- and high shares of renewable power generation (year 2030), respectively. Three groups of case studies are evaluated, one on the level of PLI integration, the second on re-allocations of renewable capacities from onshore- to offshore coordinates, and third a stress test of the PLI's performance when additional offshore wind capacity is introduced at different geographical locations.

The results establish a starting point for future research on the PLI topic. Based on the scenarios being analyzed, insights can be gained about system cost savings of a PLI, geographical needs for grid reinforcements and expansions, and where it is most cost-efficient to introduce more renewable supply capacity (onshore versus offshore). For the case presented here, a PLI gave cost saving in the magnitude of €36.8bn to €50.7bn compared with traditional, radial grid typologies. Moreover, the key players for realizing such benefits were identified to be Norway, Great Britain, and Germany. However, with support from recent literature we also stress that strongly integrated transmission projects require incentives for cooperation.

Interesting extensions of this work would include studies that incorporate more realistic boundary conditions in order to better approximate costs and benefits. For instance, building 10 to 15 transmission lines/cables are unlikely to be accepted by the public, especially for domestic grid reinforcements onshore. Moreover, accounting for uncertainty would provide a better understanding of what concerns a robust grid typology. Finally, since the PLI is expected to be close to existing gas infrastructure, a sector-coupled analysis would be a valuable contribution.

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Appendix

Table 2: Supply, demand and fuel price data from ENTSO-E Vision 4 (ENTSO-E, 2016). Onshore and offshore wind capacities are divided according to data from WindEurope (Nghiem & Pineda, 2017). CO_2 price is 76€/tonCO_2.

Supply/	Fuel price	Installed capacity [MW]					
Demand	[€/MWh_e]	BE	DE	DK	GB	NL	NO
Bio	50	2500	9340	1720	8420	5080	0
Gas	65	10040	45059	3746	40726	14438	855
Hard coal	21	0	14940	410	0	0	0
Hydro	10-30	2226	14505	9	5470	38	48700
Lignite	10	0	9026	0	0	0	0
Nuclear	5	0	0	0	9022	486	0
Oil	140	0	871	735	75	0	0
Solar PV	0	4925	58990	1405	11915	9700	0
Onshore wind	0	3518	76967	6695	27901	5495	1771
Offshore wind	0	4000	20000	6130	30000	4500	724
Total supply	-	27209	249698	20850	133529	39739	52050
Peak demand	-	13486	81369	6623	59578	18751	24468

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Paper E

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Economic and environmental benefits from integrated power grid infrastructure designs in the North Sea

Martin Kristiansen*, Magnus Korpås and Hossein Farahmand
Norwegian University of Science and Technology, Trondheim, Norway.
E-mail: martin.kristiansen@ntnu.no

Abstract. The North Sea Offshore Grid (NSOG) is considered an important contributor towards large-scale integration of renewables and electricity market coupling. Different typologies have been studied for such a multinational power grid, ranging from radial point-to-point connections to more integrated meshed typologies. An artificial island enables a high level of integration of both offshore wind power and transnational trade due to economies of scale. This paper present multiple case studies of the Power Link Island (PLI) which is visioned by TenneT in the Dogger Bank area. Our results demonstrate that the capabilities of such an island could add significant value to the system as a result of more efficient use geographically spread, cost-efficient resources. However, depending on the future level of grid integration and generation mix, the added value of a PLI varies between €0.15bn to €20bn. In addition, this could result in 18% more efficient utilization of renewable resources, primarily offshore wind, and consequently lead to significant reductions in terms of CO2 emissions.

1. Introduction

The North Sea Offshore Grid (NSOG) has been identified as one of the strategic infrastructure projects in EU Regulation No 347/2013 with the twofold purpose of integrating offshore wind resources and integrating markets for increased cross-border trade (EU Commission, 2011; European Commission, 2016). In order to speed up investments and attract private investors, financial support netting €5.35bn is provided by Connecting Europe Facility (CEF), but this is only a small portion of the estimated €140bn worth of necessary electricity infrastructure upgrades the coming decade (ENTSO-E, 2016). Several studies have addressed different grid designs and the added value of a NSOG as a result of cost-efficient utilization of variables renewable energy sources (VRES), reduced greenhouse gas (GHG) emissions, and increased security of supply (Van Hulle et al., 2009; Egerer, Kunz, & Hirschhausen, 2013; Gorenstein Dedecca & Hakvoort, 2016).

Typologies, being a combination of grid topology and technology, are traditionally divided into two groups; radial and integrated (Trötscher & Korpås, 2011; Gorenstein Dedecca & Hakvoort, 2016). A radial typology comprise point-to-point high voltage direct current (HVDC) connections, while an integrated (or meshed) typology enables multiple HVDC connections at one joint – yielding a modular and flexible design. For instance, in order to connect four countries one would need six transmission corridors in order to interlink them all with radial typology, in addition to individual offshore wind power (OWP) connections, while with an integrated typology the number of corridors is reduced from six to four (with approximately half the length, each). Additionally, an integrated typology will also achieve a higher level of utilization at each transmission corridor. The concept of a Power Link Island (PLI) is a large-scale augmentation of the integrated typology with significant potential in economies of scale (van der Meijden, 2016). According to its promoter, TenneT, a PLI can span an area of 6 km^2 and cost approximately €1.5bn for the artificial construction of the island itself; i.e. a pile of stones and sand in the shallow water of the Dogger Bank area (TenneT, 2017b).

PLI is large enough to connect 30 GW OWP capacity and by combining multiple PLIs into a so called offshore wind power hub the capacity can be expanded to 100 GW, which translates into enough energy supply for 70-100 million consumers in Europe (TenneT, 2017a). It could therefore serve an important role towards European 2050 energy and climate targets (EU Commission, 2011) – where approximately 230 GW OWP capacity is needed and 180 GW in the NSOG area (TenneT, 2017a). TenneT has announced that the PLI could be in operation already by 2035 (TenneT, 2017b), connecting Norway (NO), Denmark (DK), Germany (DE), The Netherlands (NL), Belgium (BE), and Great Britain (GB).

This paper presents multiple case studies of the PLI with data from ENTSO-E for year 2030 (ENTSO-E, 2016). Our goal is to demonstrate the added value of a PLI due to the growing interest on this topic. We do this by evaluating its performance under different system designs, i.e. a variety of possible compositions of grid and generation capacity, followed by a sensitivity analysis with respect to increasing offshore wind capacity.

2. Methodology

A mathematical optimization model for transmission and generation expansion planning is used in order to assess the impact of an artificial island in a NSOG with respect to different system designs - ranging from planned to optimal. This allows for a wide specter of case studies that are demonstrated with respect to a varying degree of OWP capacity levels.

Assumptions regarding the PLI study:

- OWP capacity is not connected to the grid in any case. Hence, we measure the system's ability to incoporate this capacity as cost-efficient as possible given a certain degree of freedom in the model (outlined by the following cases).
- No investment cost for PLI. This yields an implicit break even value when the option to utilize a PLI is active.
- No capacity restrictions for the PLI island. That is, added value might multiple/fractional number of islands.
- Domestic grid restrictions in the range of 5-15 GW. This represent a bottleneck for the offshore grid expansion.

2.1. An expansion planning model

We use a generation and transmission expansion planning (GTEP) model that is adapted to the NSOG case study. Six countries are covered in total; Norway (NO), Denmark (DK), Germany (DE), The Netherlands (NL), Belgium (BE), and Great Britain (GB), as depicted in Figure 1. The model is open-source and a documentation can be found in, e.g., (Kristiansen, Munoz, Oren, & Korpås, 2017) or (Kristiansen, Korpås, & Svendsen, 2018). Hence, only a brief introduction is given here as the model is already well documented and transparent.

The model assumes perfect competition, inelastic demand, and a welfare-maximizing system planner. Technically, it originates from a bi-level structure where generators respond to transmission investments. However, due to the aforementioned assumptions, we can recast this bi-level equilibrium model as an optimization program that co-optimize both investment- and operational costs (Samuelson, 1952). The objective is therefore to minimize total system

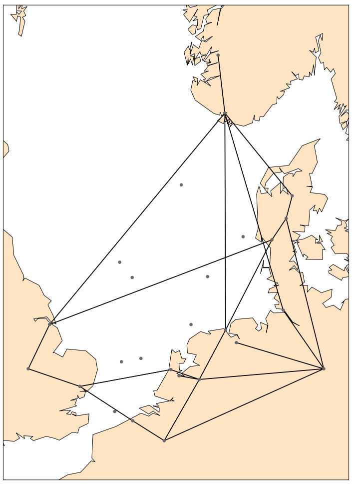


Figure 1: The North Sea Offshore Grid as it is modelled for this study. The base case excludes offshore wind connections, which are to be optimally determined by the model in the following case studies using input data from Table 1.

costs over an economic lifetime spanning 30 years. Everything is discounted back to net present value using 5% discount rate.

In order to cope with computational challenges for the resulting mixed-integer linear program (MILP), we perform k-means clustering (Härtel, Kristiansen, & Korpås, 2017) to reduce full-year time series (8760 hours) to a fraction (400 hours). Despite the dimension reduction of input data, operational system dynamics are still well represented for the interplay between, e.g., wind, solar, hydro, and load. To this end, the model captures the underlying value of the system's ability to both balance and distribute variability in terms of power balance and power flows.

We ignore Kirchhoff's voltage law (KVL) since a majority of the system infrastructure consists of high voltage direct current (HVDC) corridors that are fully controllable. This results in a transport model with no loop-flows. However, linear losses are incorporated to reflect both the transmission distance and use of necessary voltage transformers and power electronics.

2.2. Input data

We apply data from ENTSO-E (ENTSO-E, 2016) in order to replicate a future system (year 2030) with relatively high shares of variable renewables energy sources (VRES). The data is summarized in Table 1.

The variability of wind, solar, hydropower, and load is incorporated using full-year, hourly profiles from both historical data and numerical weather data, where the latter source is particularly relevant for offshore coordinates with limited historical data (Kristiansen, Korpas, Farahmand, Graabak, & Hartel, 2016).

2.3. Case study setup

The case studies are designed with the intention to cover a wide range of future, possible system designs – i.e. case (a) to (d) asserted below. That is, different levels of grid and generation mix. Our basis is the planned infrastructure for year 2030 without any OWP connections, as

Table 1: Supply, demand and fuel price data from ENTSO-E Vision 4 (ENTSO-E, 2016). Onshore and offshore wind capacities are divided according to data from WindEurope (Nghiem & Pineda, 2017). CO_2 price is 76€/tonCO_2.

Supply/	Fuel price	Installed capacity [MW]					
Demand	[€/MW$_e$]	BE	DE	DK	GB	NL	NO
Bio	50	2500	9340	1720	8420	5080	0
Gas	65	10040	45059	3746	40726	14438	855
Hard coal	21	0	14940	410	0	0	0
Hydro	10-30	2226	14505	9	5470	38	48700
Lignite	10	0	9026	0	0	0	0
Nuclear	5	0	0	0	9022	486	0
Oil	140	0	871	735	75	0	0
Solar PV	0	4925	58990	1405	11915	9700	0
Onshore wind	0	3518	76967	6695	27901	5495	1771
Offshore wind	0	4000	20000	6130	30000	4500	724
Total supply	-	27209	249698	20850	133529	39739	52050
Peak demand	-	13486	81369	6623	59578	18751	24468

depicted in Figure 1 (case (a)). In addition to this, we allow the model to find other optimal, future system designs by progressively expanding the model's option to invest in additional grid or generation capacity (case b to d). For instance, the fact that we are using a GTEP model allows us to anticipate the response from generator investments.

Our main objective is to quantify the added value of a PLI, utilizing its geographical location and economies of scale on top of each of the aforementioned system designs. This means that we first optimize for a given system design (case (a) to (d)), followed by consequent optimizations with the option to connect to a PLI. The PLI is provided for free, i.e. the offshore construction itself, while the grid connections comes at an expense. Hence, the final metrics could be viewed as break-even values for the construction of the island.

The added value of a PLI is measured with respect to the following cases:

(a) Planned cross-border capacity (Figure 1). In this scenario, the already planned infrastructure is implemented and OW can be included at a cost.

(b) Optimal cross-border capacity. Contrary to (a), we allow the model to expand cross-border capacity to an optimal level.

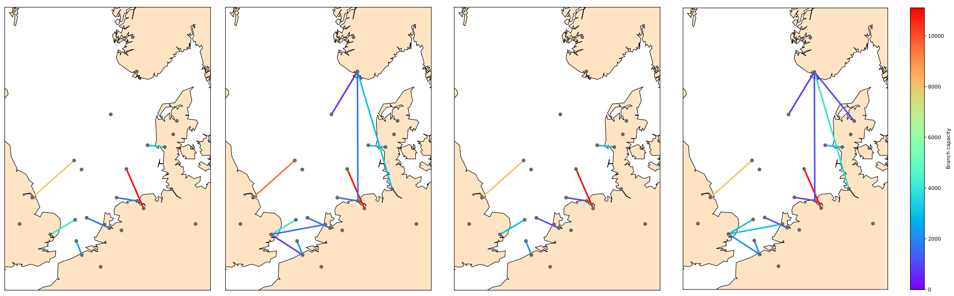
(c) Planned cross-border capacity + optimal generation mix. Expanding the possibilities in (a) to include an optimal generation mix.

(d) Optimal cross-border capacity + optimal generation mix. Expanding the possibilities in (b) to include an optimal generation mix.

2.4. Sensitivity analysis

In order to carry out a sensitivity analysis with varying shares of OWP one would need to try keeping capacity- and energy levels consistent throughout the analysis. That is, different levels of OWP from 0-100% should yield about the same system properties.

A representative substitute for the residual OWP capacity (i.e. a unit that bridges the gap from X% OWP to 100%) is, in our case, a fictive "thermal RES" unit for each country. The idea is that it should represent the marginal unit in each country with its respective properties in terms of CO2 emission rate and fuel costs, but with a yearly utilization factor equivalent to OWP. The thermal RES unit will therefore approximate the same level of capacity and yearly energy inflow as OWP. However, the main difference is the flexibility – meaning that the yearly energy can be used at any time in case of a thermal RES, whereas OWP has to follow wind speed feed-in at its respective geographical coordinate. More information about this approach can be found in (Kristiansen et al., 2018).



(a) (b) (c) (d)

Figure 2: Different scenarios for OWP integration (a)-(d) depending on underlying system design. The colored lines indicate the level of capacity investments determined by the TEP model spanning from 0 GW (purple) to 14 GW (red).

3. Results

Results are obtained for the base cases in the previous section which, in turn, is narrowed down to an impact analysis of a PLI – both in economic and environmental terms. Finally, a sensitivity analysis is presented in order to evaluate the value of a PLI under varying shares of OWP.

3.1. Different system designs with varying degree of grid and generation mix

Figure 2 shows what transmission corridors that are expanded for each of the case studies, hence the same notation (a)-(d). For instance, Case (a) comprise only of planned interconnectors without any other options than integrating its OWP capacity. This can be seen from the colormap of expanded lines in Figure 2. Note that for the planned infrastructure, the model does not find it beneficial to incorporate OWP in NO as the costs for grid connection exceeds the operational cost savings. This means that all OWP production in NO is curtailed. This observation is also true for Case (c), i.e. planned infrastructure with generation capacity expansion.

Contrary to the planned infrastructure cases, Figure 2 clearly illustrates that it is more beneficial to include OWP when we allow for optimal cross-border transmission capacity. This is because the increased trade capacity from NO to the continent and GB results in more trade options at a relatively higher price.

One occurring observation for all four cases is that the ones with generation expansion does not deviate too much from the ones without, in terms of infrastructure investment portfolio. This can be seen by comparing (a) with (c), and (b) with (d) in Figure 2. However, it might have a more evident impact on economic- or environmental metrics.

3.2. The typologial impact of a PLI

The four base cases represented in Figure 2 are in Figure 3 considered with the option to utilize a PLI in the Dogger Bank area. Hence, the added value of such an option can be quantified. The PLI functions as a transnational transportation hub in addition to including offshore wind

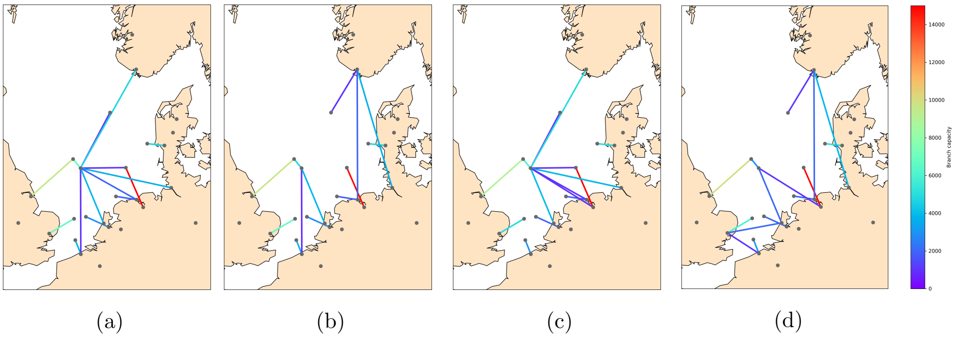


Figure 3: Case (a)-(d) including the option to utilize a free PLI. The colored lines indicate the level of capacity investments determined by the TEP model spanning from 0 GW (purple) to 14 GW (red).

resources. Note that the OWP capacity in NO is included for all cases, contrary to the base cases where we excluded the option to use a PLI (see Figure 1).

For the planned infrastructure and generation mix, Case (a), about 31 GW of new transmission capacity is built to the PLI – including both offshore wind and transnational trade capacity. This is approximately equivalent to €28bn worth of investments, in terms of additional investments exceeding the base case. However, the operational cost savings are almost 60% higher netting €48bn. This means that the added value is around €20bn for Case (a).

The other three cases leads to smaller amounts of cost savings and the most influential factor is grid expansion. Case (b) assumes that, by year 2030, cross-border transmission corridors reach an optimal capacity level determined by the model (exceeding case (a) with 11.4 GW in total). With this, the existing grid reach a way more efficient system operation than Case (a) which, consequently, means that the value potential for a PLI concept dacay. The added value of a PLI in Case (b) is as low as €0.15bn since the model sees other competitive expansion alternatives.

By trying to anticipate changes in the generation mix, i.e. Case (c) and (d), Figure 3 shows that the two latter cases result in almost the same grid typologies as when ignoring changes in the generation mix (Case (a) and (b)). The value of a PLI does, however, deviate considerably. As expected, the added value in Case (c) is lower than for Case (a) as it is reduced to €15bn. But, for Case (d), the added value is higher than for Case(b) reaching almost €1bn.

Among changes in grid and generation, grid is definitely the most influential one in terms of its impact on the profitability of a PLI. Hence, the value of a PLI would most likely depend on the future development of the NSOG to a larger extent than changes in the generation mix.

3.3. Sensitivity analysis with variable shares of OWP

A sensitivity analysis is performed in order to get more in-depth insights to the added value of a PLI – both in terms of cost savings and reductions in CO2 emissions. An important driver for these values, given the outline for our case studies, is the share OWP capacity. As a result, a wide range of OWP capacity levels are evaluated spanning from 0 GW to double the amount of our input data, i.e. up to 2x65 GW. The horizontal axis in Figure 4 and Figure 5 does therefore vary with respect to the aforementioned range of capacities, where 100% is equivalent to 130 GW OWP. Peak demand is, in comparison, around 204 GW.

First, note that 50% OWP share should yield approximately the same results as obtained in the previous analysis since it represents the same amount of OWP as in the original data input.

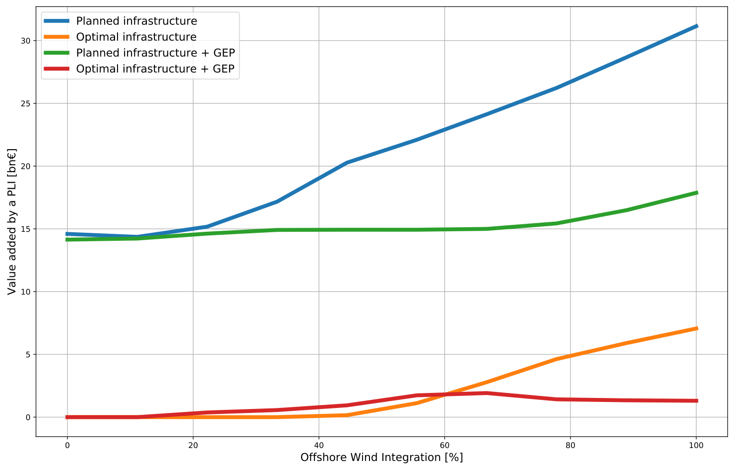


Figure 4: The value of a PLI under an increasing share of OWP ranging from 0 GW to twice the capacity as the original input data from ENTSO-E Vision 4 (i.e. 130 GW).

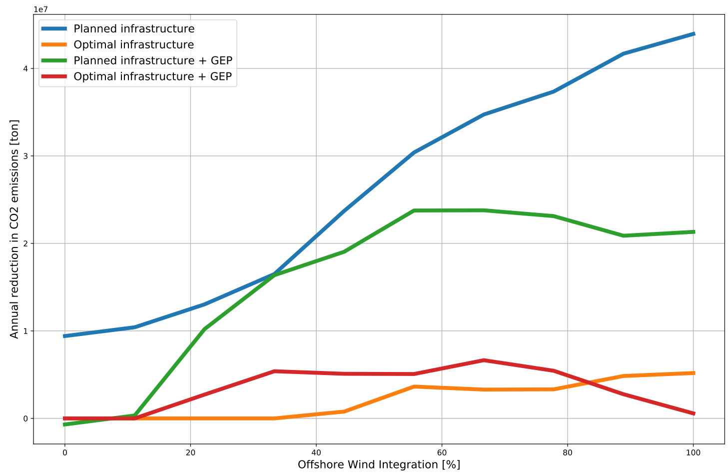


Figure 5: The CO2 emission impact of a PLI under an increasing share of OWP ranging from 0 GW to twice the capacity as the original input data from ENTSO-E Vision 4 (i.e. 130 GW).

However, due to the use of a fictive thermal RES unit, the results might deviate slightly. For instance, Figure 4 implies that the added value of a PLI is around €21bn (which is supposed to be closer to €20bn). However, the goal with the sensitivity analysis is rather to visualize the relative impact of a PLI under different system designs (Case (a)-(d)) and different OWP capacity levels.

As expected, the value of a PLI in Case (a) comprise a steeper increase with respect to an increasing share of OWP compared with the other cases. This observation is even more conspicuous for CO2 emission reductions, as seen from Figure 5. This could imply the important role a PLI plays as a transnational transmission hub, ensuring high utilization of renewable resources by providing a high degree of spatial flexibility.

4. Conclusion

This paper evaluates different degrees of grid integration for a North Sea Offshore Grid (NSOG), with a particular focus on the economic impact of an artificial island compared to traditional solutions such as radial grid typologies. Results are obtained using a transmission and generation expansion planning model incorporating data that reflects a future power system in year 2030 with relatively high shares of renewable supply capacity. With this, we are able to evaluate how different degrees of grid integration manage to utilize variable energy sources, such as offshore wind, in addition to transnational trade.

Sensitivity analyses are presented in order to assess the added value of an artificial island under varying capacity levels of offshore wind power ranging from 0-200% of the original input data (ENTSO-E Vision 4). A fictive thermal unit is used for the analysis in order to approximate consistent energy- and capacity levels in the system for all shares of OWP.

The presented work gives deeper insights on the topic concerning the construction of an artificial island in the NSOG and its potential range of added value to the system. The value range is determined by different degrees of grid and generation mix capacity, i.e. for a planned and optimal offshore infrastructure, and for a estimated and optimal generation mix. To this end, one is able to assess the landscape of opportunities for a PLI.

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Paper F

Paper F

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A generic framework for power system flexibility analysis using cooperative game theory

Martin Kristiansen[a,*], Magnus Korpås[a], Harald G. Svendsen[b]

[a] Norwegian University of Science and Technology, Trondheim, Norway
[b] SINTEF Energy, Trondheim, Norway

HIGHLIGHTS

- Alternative method for flexibility analyses using Shapley Value.
- The method is demonstrated with a multinational offshore grid case study.
- Demand for flexibility options are identified by countries and technology.
- Implicitly accounting for uncertainty in lead time and innovation.
- Generate insights for multinational policy designs or investment analyses.

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Renewable integration
Shapley value
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ABSTRACT

Electricity grid infrastructures provides valuable flexibility in power systems with high shares of variable supply due to its ability to distribute low-cost supply to load centers (spatial), in addition to interlinking a variety of supply and demand characteristics that potentially offset each others negative impact on system balance (temporal). In this paper, we present a framework to investigate the benefits of alternative flexibility providers, such as fast-ramping gas turbines, hydropower and demand side management, by using a generation and transmission capacity expansion planning model. We demonstrate our findings with a multinational case study of the North Sea Offshore Grid with an infrastructure typology from year 2016 and operational data for year 2030 – considering a range of renewable capacity levels spanning from 0% to 100%. First, we show how different flexibility providers are allocated geographically by the model. Second, operational cost savings are quantified per incremental unit of flexible capacity. Finally, we present a way to rank different flexibility providers by considering their marginal contribution to aggregate cost savings, reduced CO_2 emissions, and increased utilization of renewable energy sources in the system. The Shapley Value from cooperative game theory allows us to assess the latter benefits accounting for all possible sequences of technology deployment, in contrast to traditional approaches. The presented framework could help to gain insights for energy policy designs or risk assessments.

1. Introduction

The European power system is exposed to large-scale integration of renewables the coming decades [1], demanding more flexibility in order to distribute, consume, or store variable levels of power feed-in [2]. An adequate grid infrastructure can contribute with spatial flexibility by distributing power surpluses over larger geographical areas, which in turn connects the variable generation to distant load centers and potential energy storage (temporal flexibility) reducing system imbalances [3]. Hence, increased flexibility in both space (spatial) and time (temporal) could be achieved with grid expansion. In addition to a more efficient use of clean resources and decreased green house gas (GHG) emissions, this is the reason why the North Sea Offshore Grid (NSOG) has been identified by the EU Commission as one of the strategic trans-European energy infrastructure priorities in the EU Regulation No 347/2013. Potentially serving the twofold purpose of integrating offshore wind power generation while, at the same time, facilitating for increased cross-border trade.

Spatial and temporal flexibility are a key elements to maintain security of supply and ensuring cost-efficient utilization of variable renewable energy sources (VRES) feed-in [4]. More electricity grid is needed in order to reach future energy- and climate targets and ENTSO-

* Corresponding author.
E-mail address: martin.kristiansen@ntnu.no (M. Kristiansen).

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E estimates €150bn worth of pan-European energy infrastructure investments the next decade, with current supply and demand projections. A large share these investments comprise multinational electricity grid expansion [5]. One of the main challenges when it comes to planning for such investments is the geographical span that needs to be considered [6]. That is, by connecting larger geographical areas through an infrastructure means that multivariate characteristics from multiple countries, with their respective supply- and demand mix, has to be accounted for in order to capture underlying values of larger system dynamics. For instance, the synergy value of VRES, such as offshore wind in the coastal areas of Great Britain, and energy storage facilities, such as hydropower located in the Norwegian mountains [7].

The geographical span does not only affect the computational complexity in long-term planning models, but it also induces tighter market integration between countries. When building a new, or expanding an old, transmission corridor – price effects will occur at adjacent connection points [8]. These adjacent points are, in our case, countries that experience a change in welfare, i.e. consumer surplus and producer surplus. In turn, this might lead to impact on neighbouring regions or countries as shown in [9] focusing on distributional effects of transmission expansion. In Egerer et al. [10] they study the welfare implications of grid expansion in the NSOG. Other similar studies, but in context of renewable portfolio standards, includes an assessment of the Western Electricity Coordinating Council (WECC) in the US [11].

Evaluating the need for, and impact of, flexibility options is thus a complex task considering the size and dynamics of a power system, and its economic implications. Moreover, as technology matures and costs decreases, other flexibility options might evolve as cost competitive compared with grid expansion. Hence, there is an uncertainty element that should be incorporated when assessing the added value of flexibility sources over a long economic lifetime [12]. For instance, the deployment sequence of different flexibility providers might have an economic impact on previous, and future, deployments of other technologies.

This paper presents a generic framework for geographical- and economic evaluation of flexibility options. We use a generation and transmission expansion planning (GTEP) model and leverage methods from cooperative game theory [13] in order to cope with the aforementioned context. More precisely, we exploit the properties of The Shapley Value (SV) [14] in order to account for different deployment sequences and, consequently, use this information to assess the contribution from each flexibility provider to system benefits. To this end, we are able to somewhat account for future uncertainty in, e.g., innovation and deployment sequence without the need of sophisticated, stochastic programming tools. However, we do not claim that the presented approach is a substitute for the latter – rather a complement. We demonstrate the added value in terms of more insights to the problem at hand.

The remaining parts of this paper is structured as follows. Section 2 overviews existing literature on how to quantify the need for system flexibility and its contributions on system level, extended with recent work on cooperative game theory for power system applications. Section 3 presents the GTEP expansion planning model, case study setup, and a brief introduction on how the SV is calculated. Finally, results from the NSOG case study is presented in Section 4 followed by a conclusion with recommendations for future work in Section 5.

2. Literature

This section overviews existing literature and power system flexibility analyses, with a particular focus on long-term planning models that are used for GTEP. Together with a review on relevant applications of cooperative game theory, we derive our contributions in the end of the section.

2.1. Long-term planning models and flexibility analysis

As already mentioned in the introduction, novel GTEP models has to incorporate a significant level of details in order to account for current and future market characteristics. At the same time, they have to include larger geographical areas as discussed in prominent TEP reviews by Lumbreras and Ramos [6] and, with a focus on multinational offshore grids like the NSOG by Gorenstein Dedecca and Hakvoort [15]. It has been shown that there is an underlying value in capturing system dynamics over larger areas due to smoothing effects [16]. For instance, by aggregating VRES generation over a larger geographical area the net feed-in on system level tends to be smoother than for smaller areas due to weather variations. This effect could offset some need for flexibility, at least temporal, whereas spatial flexibility has to be in place in order to link those interdependencies.

Moreover, the material price impact of lumpy grid investments creates incentives for generators to respond with changes in their generation mix due to potential price arbitrage [8], meaning that cost-efficient equilibria are not met if not considering both transmission and generation expansion due to its synergies on cost recovery [17]. Other challenges in the GTEP literature include, but is not limited to, incorporation of uncertainty [18], representation of loop flows [19], distributed generation, demand side management, detailed energy storage handling, and FACTS devices [20]. The main challenge is that operational details comes with an expense of the larger and more complex optimization programs, consequently leading to mathematical difficulties such as non-convexity and intractable models.

Flexibility is referred to as the key term of the future by Auer and Haas [2] and has received increasing attention over the last years. One occurring topic is the mapping of different metrics to quantify the level of flexibility in a power system [21]. High-level metrics such as peak demand, regional grid strength, interconnections with other areas, the number of power markets, and the generation mix are identified as the most important ones [4]. Subsequently, this could be broken down to individual flexibility providers such as demand side management (DSM), fast-ramping generators, or energy storage. A comprehensive review of different technologies and strategies is presented in [3].

The most prominent contributor to a cost-efficient and reliable development of the power system is grid expansion. This has been demonstrated for the European case by Fürsch et al. [22]. Moreover, Huber et al. [23] has investigated short-term aspects of flexibility on an hourly scale with different levels of VRES and geographical span, concluding that flexibility needs are smaller for interconnected, transnational power systems. The same conception of grid infrastructures being a significant contributor to the availability of flexibility, both in temporal and spatial form, is shown by Lannoye et al. [24] using Insufficient Ramping Resource Expectation (IRRE) and the Periods of Flexibility Deficit (PFD) as explanatory metrics. However, uncertainty is left out of scope in the aforementioned literature.

Konstantelos and Strbac [12] acknowledge that transmission grid investments are important for the future power system development, but questions its competitive edge compared with other flexible network technologies. They demonstrate the value of incorporating multiple flexibility options where costly grid reinforcements could be avoided, and that models ignoring uncertainty could systematically undervalue benefits of flexibility options. The approach of considering multiple options under uncertainty has reached a consensus as one of the most frequent shortcomings in the existing literature [25]. The latter review paper highlights learning curves and innovation, where a majority of planning models, especially static ones, might yield inefficient lock-in of established technology options. In this paper, we will to some extent account for the reviewed shortcomings, by utilizing a relatively simple approach compared to using, e.g., a multi-stage stochastic program or robust optimization.

2.2. Cooperative game theory in power system applications

Cooperative game theory has been used for various applications in power systems and dates back to Hobbs and Kelly [26] analyzing fair transmission pricing policies, followed by the first applications on transmission expansion planning by Contreras and Wu [27] calculating fair cost allocations. Both papers applies The Shapley Value [14] in order to find fair solutions with respect to marginal contributions from each player entering full cooperation (grand coalition), in all possible sequences, for a N-player game. Other applications in power systems include the allocation of firm energy rights among hydro plants [28] and benefit-based expansion cost allocation in context of renewable integration [29]. All with players whose incentives are to maximize their own payoff, which is somewhat different from our approach viewing players as technologies (flexibility options) under multi-national welfare maximization.

In recent years, there has been an increasing amount of applications in distribution systems. For instance, profit allocations among distributed energy sources acting as virtual power plants [30], remuneration to participants in demand response programs [31], or for calculating fair allocations of costs and benefits among microgrid agents [32]. Still, no applications considering flexibility technologies.

Banez-Chicharro et al. [33,34] views transmission projects as players using an extension of the SV approach, called Aumann-Shapley (AS). The main difference between the SV and AS is that the latter accounts for fractional contributions from different players, in addition to being easily scalable to larger problems [35]. Although computational efforts is not an issue in this paper, there are other properties of AS that might be beneficial for studies like the one presented in this paper. We will discuss this later.

2.3. Contributions

We extend the reviewed literature by applying SV in context of power system flexibility analysis, defining flexibility providers as players in a N-person cooperative game. Moreover, our generic step-by-step approach is demonstrated with a North Sea Offshore Grid case study highlighting the added value and insights that could be gained. This with limited information about future costs and decision support tools that easily could be solved with off-the-shelf software. Hence, our contribution is two-folded:

1. Present an approach for a comparative analysis of different levels of VRES, while maintaining consistent capacity- and energy levels in the system.
2. Apply the SV from cooperative game theory in order to evaluate the competitive edge of transmission capacity as a flexibility provider, compared with other potential flexibility options.

This means that we also are able to cope with some of the most frequent shortcomings in the existing literature. That is, present alternative ways to account for uncertainty in learning and innovation, using a GTEP model that incorporates multivariate correlations in load and variable generation as opposed to static models [25].

3. Methodology

To carry out the evaluation of different flexibility options we use a GTEP model (PowerGIM). In turn, we use results from this model in order to calculate the SV. The GTEP model is based an extension of the planning models in [36] and more recently [37], which is available online in the same git repository as the pan-European market simulator; PowerGAMA [38]. A list of notations for the GTEP model presented in following subsections can be found in Appendix A.

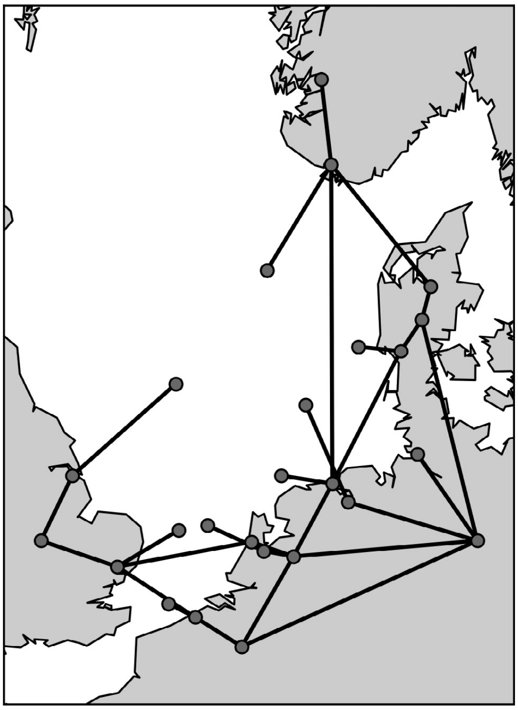

Fig. 1. Base case for North Sea grid infrastructure (year 2016). Demand and generation capacities are given for year 2030 [40].

3.1. Generation and transmission expansion planning model

The mathematical formulation, (1a)–(1k), is adapted to the 25-bus NSOG case study comprising six countries in total, namely; Norway (NO), Denmark (DK), Germany (DE), The Netherlands (NL), Belgium (BE), and Great Britain (GB), as depicted in Fig. 1.

The model originates from a bi-level structure where generators respond to transmission investments. Due to assumptions of perfect competition, inelastic demand and a welfare maximizing transmission infrastructure investor, we can recast this bi-level equilibrium model as an optimization program that co-optimize both investment- (IC) and operational costs (OC) [39]. In turn, we assume that investment costs (1b) and market operation (1c) reach cost-efficient equilibrium by minimizing the net present value (NPV) of total system costs (1a) measured in €. Operational costs are calculated for one representative year, multiplied with an annuity factor a in order to convert annual costs to NPV.

$$\min_{x,y,z,g,f,s} \quad IC + a \cdot OC \tag{1a}$$

where

$$IC = \sum_{b \in B} (C_b^{fix} y_b^{num} + C_b^{var} y_b^{cap}) + \sum_{n \in N} CZ_n z_n + \sum_{i \in G} CX_i x_i \tag{1b}$$

$$OC = \sum_{t \in T} \omega_t \left(\sum_{i \in G} (MC_i + CO2_i) g_{it} + \sum_{n \in N} VOLL s_{nt} \right) \tag{1c}$$

$$C_b^{fix} = B + B^d D_b + 2CS_b \quad \forall\ b \in B \tag{1d}$$

$$C_b^{var} = B^{dp} D_b + 2CS_b^p \quad \forall\ b \in B \tag{1e}$$

subject to

$$\sum_{i\in G_n} g_{it} + \sum_{b\in B_n^{in}} f_{bt}(1-l_b) - \sum_{b\in B_n^{out}} f_{bt} + s_{nt} = \sum_{l\in L_n} D_{lt} \quad \forall\ n,t \in N,T \tag{1f}$$

$$P_i^{min} \leqslant g_{it} \leqslant \gamma_{it}(P_i^e + x_i) \quad \forall\ i,t \in G,T \tag{1g}$$

$$\sum_{t\in T} \omega_t g_{it} \leqslant E_i \quad \forall\ i \in G \tag{1h}$$

$$-(P_b^e + y_b^{cap}) \leqslant f_{bt} \leqslant (P_b^e + y_b^{cap}) \quad \forall\ b,t \in B,T \tag{1i}$$

$$y_b^{cap} \leqslant P_b^{n,max} y_b^{num} \quad \forall\ b \in B \tag{1j}$$

$$\sum_{b\in B_n} y_b^{num} \leqslant M z_n \quad \forall\ n \in N \tag{1k}$$

$$x_i, y_b^{cap}, g_{it}, s_{nt} \in \mathbb{R}^+, \quad f_{bt} \in \mathbb{R}, \quad y_b^{num} \in \mathbb{Z}^+, \quad z_n \in \{0,1\}$$

The GTEP model is targeted for system characteristics in the North Sea region where both offshore grid technology costs and hydro representation plays an important role. Eqs. (1d) and (1e) represents the fixed- and variable cost functions, respectively, incorporating distance and power rating, denoted d and p, in addition to end-point switch-gear costs, CS. The fixed costs, C_b^{fix}, are multiplied with the number of new cables, y_b^{num}, and the variable costs, C_b^{var}, with the accumulated new cable capacity, y_b^{cap}, as shown by (1b). Moreover, in cases where new nodes, e.g. offshore platforms, needs to be installed we use a binary variable, z_n, that is enforced by new cables connected to this node (1k). Finally, generation expansion is represented by continuous variables, x_i, which all together with operational variables for generation, g_{it}, branch flow, f_{bt}, and load shedding, s_{nt}, yield a mixed-integer linear program (MILP).

We ignore Kirchhoff's voltage law (KVL) since a majority of the system infrastructure consists of high voltage direct current (HVDC) branches that are fully controllable. This results in a transport model with no loop-flows (1i). However, linear losses are incorporated to reflect both the transmission distance and use of necessary voltage transformers and power electronics, as seen from the nodal energy balance (1f), i.e. Kirchhoff's current law (KCL). The nodal energy balance (1f) ensures that demand is met by the sum of generation, power flow, and/or load shedding, in each country. Hence, input data is given at national level using a discount rate amounting to 5% and an economic lifetime spanning 30 years [40].

The variability of wind, solar, hydropower, and load is incorporated using full-year, hourly profiles from both historical data and numerical weather data, where the latter source is particularly relevant for offshore coordinates with limited historical data [41]. The hourly profiles are reflected in (1g) with a factor, γ_{it}, ranging from 0 to 1 inflow/availability and multiplied with the maximum existing capacity, P_i^e, plus any additional capacity investments, x_i. We use agglomerative hierarchical clustering technique in order to reduce the hourly time series from 8760 h to $8760/2^4 = 548$ h, while still maintaining a relatively high level of multivariate correlations between the time series and between the different geographical coordinates [42,43]. This improves the models ability to capture underlying values of smoothing effects and variable flow patterns at system level.

3.2. Varying the share of renewables from 0% to 100%

All flexibility options are evaluated under different shares of renewable capacity. The base case renewable capacity is given by ENTSO-E Vision 4 [40], i.e. 100% VRES will be equivalent to this data set. For 0% VRES, the base case VRES capacity is allocated over to a fictive *RES-thermal* generator restricted by yearly energy inflow (1h) corresponding to the capacity-weighted average of all VRES inflow (yielding an average utilization factor 0.34); offshore wind, onshore wind, and solar PV. Hence, the available capacity and yearly energy inflow is about the same for all cases with VRES capacity ranging from 0% to 100%. Moreover, RES-thermal capacity operates with a marginal cost (37.30 €/MW h on average) and CO2 emission rate (0.31 tonCO_2/MW h_e on average) equal to the most expensive thermal generator in each country. The latter approach is used to reflect the operational costs of switching a share of the peak (thermal) capacity mix from dispatchable to variable, utilizing the merit-order effect in each country.

3.3. Incorporating multiple flexibility options

The following assertions describes the different case studies. Each case study is ran with the GTEP model including, and excluding, the option to invest in new capacity under a varying share of VRES capacity as discussed in the previous subsection. This means that each level of VRES is evaluated with, and without, the option to invest in additional capacity. Moreover, investment costs are set to zero, meaning that the marginal impact on system operation does not reflect investment costs, but could rather be viewed as break-even thresholds. Hence, our approach is independent of capital cost data.

1. *Grid:* Grid investments are the only options that increase availability of both temporal and spatial flexibility, simultaneously, among the considered alternatives. We allow radial typologies for offshore HVDC interconnectors, and onshore AC grid reinforcements. Capacities to offshore wind nodes are kept fixed at a high level in order to isolate those from the analysis.
2. *Gas CCS:* Fast-ramping gas units with carbon capture and storage (CCS) technology can be utilized to balance out the increasing mismatch between VRES power feed-in and demand. We assume that the generators are available at full capacity, all hours during the year.
3. *DSM:* Demand side management (DSM) is simply included as generation capacity at a marginal cost equivalent to the levelized costs of saved energy (LCSE), approximately 45 €/MW h [44]. The maximum capacity of this flexible load is restricted to 10% of the average load for a given country over a full year.[1] Hence, only a small portion of the total load is assumed to be flexible, while the rest of the load can be curtailed at a price ceiling amounting to 1000 €/MW h (VOLL).
4. *Hydro:* We disregard pumping in this case study, meaning that we can only invest in additional hydropower production capacity. Additional capacity is restricted to 10% of the capacity provided by Vision 4, and the yearly utilization is restricted to 50% where we use time-series to reflect the seasonal variation in water value (i.e. marginal costs).[2] Note that Norway is the only country that possess any considerable amount of hydro in this data set.
5. *Combined:* The aforementioned options (1–4) are included in groups, or all together. The GTEP model expands the most cost-efficient option(s), accounting for both spatial- and temporal benefits. The case when all options are considered together represents what is referred to as the grand coalition in cooperative game theory. The SV will account for all possible ways to reach this grand coalition.

3.4. The Shapley value

The SV is a method that calculates allocations of costs or benefits that are considered to be fair for cooperative solutions. A famous example is The Airport Game [47] where the SV is used to calculate a fair airfield maintenance fee to airplanes of different sizes, i, since each

[1] Applications of DSM is expected to reduce peak load with 13% and, if combined with demand response (DR), its potential increases to 17.4% in year 2020 [45]. This corresponds to 10.3% reduction in yearly energy consumption.

[2] The capacity expansion potential and yearly energy disposal are based on data from ENTSO-E Vision 4 [40], in addition to an assessment of Norway as a green battery in 2030 [46], studying the potential for hydropower expansion.

airplane has different impact on airfield requirements and maintenance cost. Another example is The Bankruptcy Game [48] where a small company owes money to creditors, i, but the remaining assets cannot cover the total debt. Here, the SV is used to find a fair allocation of debt payback to creditors, considering the average value of all possible paybacks to creditors with remaining company values.

In this paper, we think of different flexibility providers as players, i, and assess their contribution towards a solution where all technologies are deployed in the power system. To this end, the SV will account for different sequences in which technologies are deployed, which makes sense from a perspective of uncertainty regarding learning and innovation, as well as lead-time. For instance, some technologies (e.g. grid) might require a longer lead-time from day of decision to day of operation, compared to other alternatives (e.g. gas plants). The SV for a given technology, i, is shown in Eq. (2).

$$\phi_i(N,v) = \frac{1}{|N|!}\sum_{S\subseteq N\setminus\{i\}} |S|!(|N|-|S|-1)![v(S\cup i)-v(S)] \tag{2}$$

The characteristic functions $v(\cdot)$ in Eq. (2) are collected for each possible combination of flexibility options from the GTEP model. The procedure for calculating the SV is; weight different ways where technology i can add value to a combination of technologies S, which is a subset of all technologies N (grand coalition). This captures the marginal contributions from technology i for different sequences, $[v(S\cup i)-v(S)]$, weighted by the $|S|!$ different ways the combination S could have been formed prior to technology i joining it and by the $(|N|-|S|-1)!$ ways the remaining technologies could join the same coalition, summed over all combinations of subsets excluding i ($S \subseteq N\setminus\{i\}$) and averaged by dividing with $|N|!$, where $|N|!$ is the number off possible orderings of all technologies. The resulting payoff, in our case contribution to system benefits, is given by $\phi_i(N,v)$ for each technology i.

This means that the GTEP model optimize expansion plans considering availability of different flexibility options, individually (as i) and in combinations with each other (as S or N). Another alternative is to let the GTEP model decide which flexibility alternatives to invest in, in one run, equivalent to the grand coalition, N, hereby referred to as the traditional approach. The latter will differ from the SV since it ignores aspects of ordering and technologies' contribution to smaller subcoalitions, $S \subset N$.

Note that the GTEP model will expand bulky capacities of different flexibility options, e.g. 1000 MW grid. This is where AS differs from SV, whereas the former calculates the marginal contributions by uniformly increasing the size of different flexibility providers from zero to its current value. For instance, other flexibility options are included before grid reach a bulky value of 1000 MW. However, since our GTEP model contains integer variables we cannot exploit sensitivity information from its capacity constraints (dual variables), which is necessary in order to use AS. One could, of course, relax all integer variables in the GTEP model.

3.5. Measuring the benefits of flexibility providers

Based on the case study setup presented in the previous subsections, we quantify the benefits of different flexibility providers with the GTEP model. This is done for different levels of VRES, ranging from 0% to 100%. The benefits are simply measured in relation to the base case GTEP results, i.e. where flexibility options are excluded. For instance, when considering the impact of grid expansion, we simply calculate the difference from the base case, which most likely involve higher operational costs due to grid congestion.

In the following results section we present (i) the geographical need for flexibility options, (ii) the marginal value of each flexibility provider at system level (cost savings per unit capacity), and (iii), the accumulated system benefits from each flexibility provider (total cost savings, emission reductions, VRES utilization). The latter is calculated in two ways; first with respect to one GTEP optimization with all flexibility options available, and second, calculating the SV based on $2^4 = 16$ different GTEP optimizations, i.e. different combinations ($S \subseteq N$) of the four flexibility providers.

4. Results

First, a brief discussion of the base case is presented, followed by our findings on the metrics listed in the end of previous section.

4.1. Base case

The base cases comprise 0, 25, 50, 75, and 100% VRES excluding the option to invest in flexibility. We use current grid typology from year 2016, and generation and demand for 2030 [40], yielding inefficient grid capacity. However, we allow for load shedding at VOLL €/MW h.

With low shares renewables in the system, the supply mix is perfectly able to balance with load due to the availability of RES-thermal, which is more flexible than the original VRES capacity although the yearly energy availability is approximately the same. However, RES-thermal can be dispatch freely over all hours, in contrast to VRES that is bounded by its energy inflow (e.g. wind speed). There is zero load shedding in the system, but the dispatch comprise of a more costly generation mix as well as high emission levels in contrast to system operation with high levels of VRES.

For each base case with different shares of VRES, we consider all possible flexibility options and quantify their impact on system operation, alone and in combination with each other. For instance, if we allow for grid expansion, we see that more grid is introduced as the share of renewables increase, yielding lower average price levels and, at the same time, higher price volatility due to more variable supply capacity. This is also in line with the reviewed literature. However, note that grid will have a smoothing effect on price variations, i.e. it is the level of VRES that is the main driver for price volatility.

Throughout the remaining parts of this section the low- and high VRES scenarios represents 25% and 100% VRES capacity, respectively, relative to ENTSO-E Vision 4 [40].

4.2. Geographical spread of flexibility needs

Fig. 2 illustrates how the flexibility needs are allocated by technology and by country. The left part of the figure shows the allocation under low shares of renewables where, for instance, interconnectors (i.e. cross-border) grid expansion is allocated in larger portions to NO and GB (see upper left plot) while a majority of total DSM capacity is deployed in DE, in addition to hydropower and gas CCS. The upper right plot, i.e. with high share of renewables, shows approximately the same capacity allocation to each country, although grid investments seems to be more evenly distributed between countries bordering the northern part of the North Sea. The latter reflects the need for a geographically interlinked system exploiting smoothing effects and multivariate correlations in supply and demand.

Note that hydro stays about the same in both cases due to its resource restrictions (we assume that each country can only expand 10% of the given capacity in Vision 4). Moreover, hydropower is not expanded at all in NO due to its already high capacity surplus (52 GW) and cross-border trade limitations (2.4 GW). Hence, grid would be the first priority from NO's perspective given the input data.

In order to get a full overview of the allocations in each case, i.e. for low and high renewable shares, we need to also consider the relative capacity allocation within a country. This is depicted in the lower part of Fig. 2. One occurring observation for most countries is the shift from DSM and gas CCS to grid expansion when the share of variable generation capacity increase. A justification for this shift could be that grid

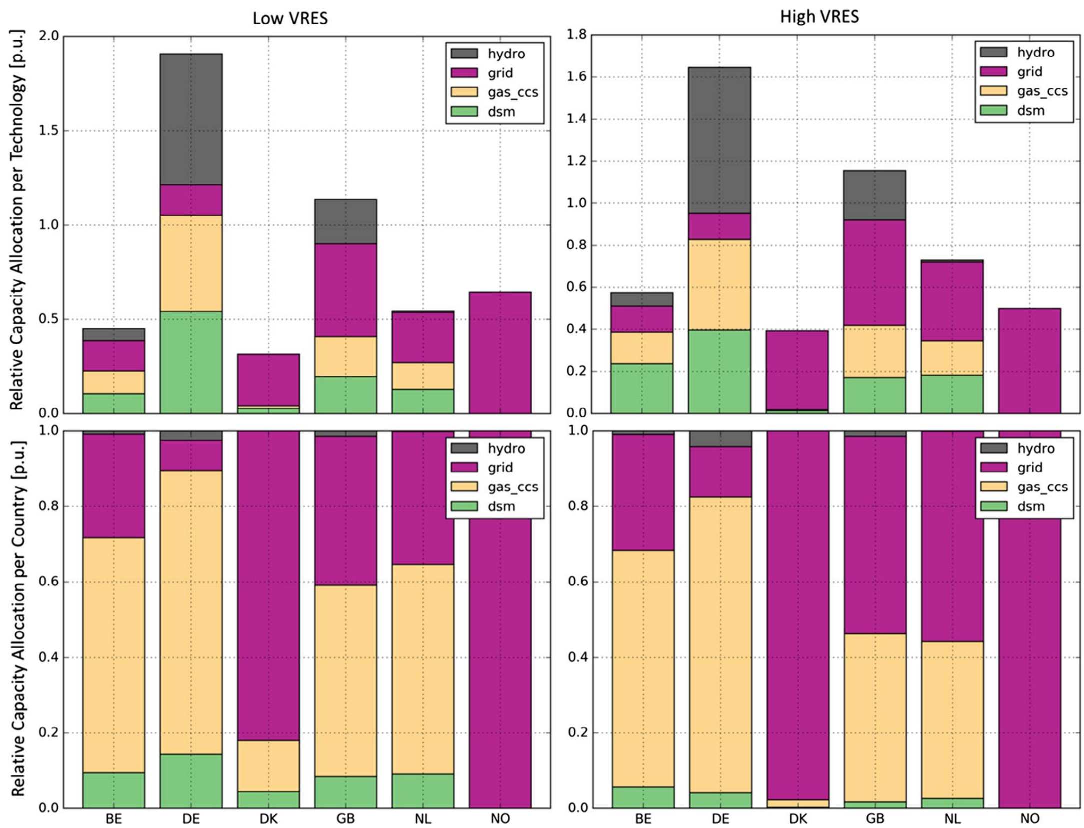

Fig. 2. Relative capacity by technology (upper plots) and by country (lower plots) under low share (left part) and high share (right part) of renewables. Relative values sums to one. Input data from ENTSO-E Vision 4 [40].

provides both spatial and temporal flexibility, as discussed earlier. The latter observation is most significant for DK and yields higher availability of cost-efficient supply in the system.

In summary, Fig. 2 demonstrates that the geographical distribution of different flexibility providers remains more or less stable when comparing low- and high share of VRES. However, all countries weight their domestic flexibility mix towards more grid when the share of VRES increases, which is in line with the findings in, e.g., Lannoye et al. [24].

4.3. Marginal value of each flexibility provider

Individual flexibility providers are assessed in a system context by quantifying its marginal impact on operational costs, as shown in Fig. 3. One can see from the figure that the marginal value of gas CCS is declining for increasing shares of variable generation capacity, substituted by an increasing value tradeoffs with grid interconnections, and partly DSM. The latter stays about constant at m0.9€/MW for all shares of renewable capacity in the system, while the marginal value of grid interconnections increases with almost 10%.

The most risky flexibility option seems to be gas CCS. Its relatively high fuel cost makes it less competitive when low-cost VRES is introduced through import from transmission corridors that are connected with, e.g., NO and DK. As a result of grid expansion, the average price levels converge and might drop below the marginal cost of gas CCS.

The marginal value of hydropower per capacity unit is naturally

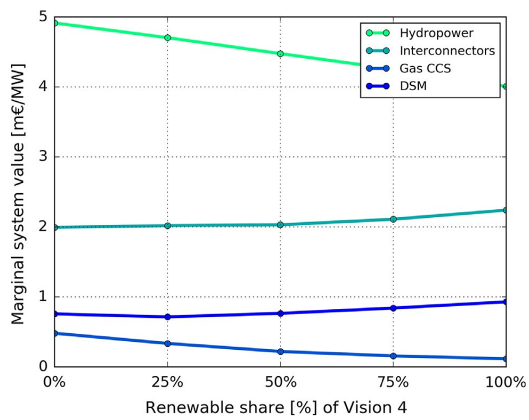

Fig. 3. The marginal value per unit capacity (m€/MW) for each flexibility provider in terms of operational cost savings at system level.

high due to (i) its limited expansion possibilities, both by region and by capacity (10% of initial capacity levels), and (ii), its low marginal costs which lies in the "safe" region of the merit-order supply curve. However, the value decreases significantly when additional VRES capacity is added to the system, since the price volatility caused by solar and wind substitutes some hydropower generation (for instance during

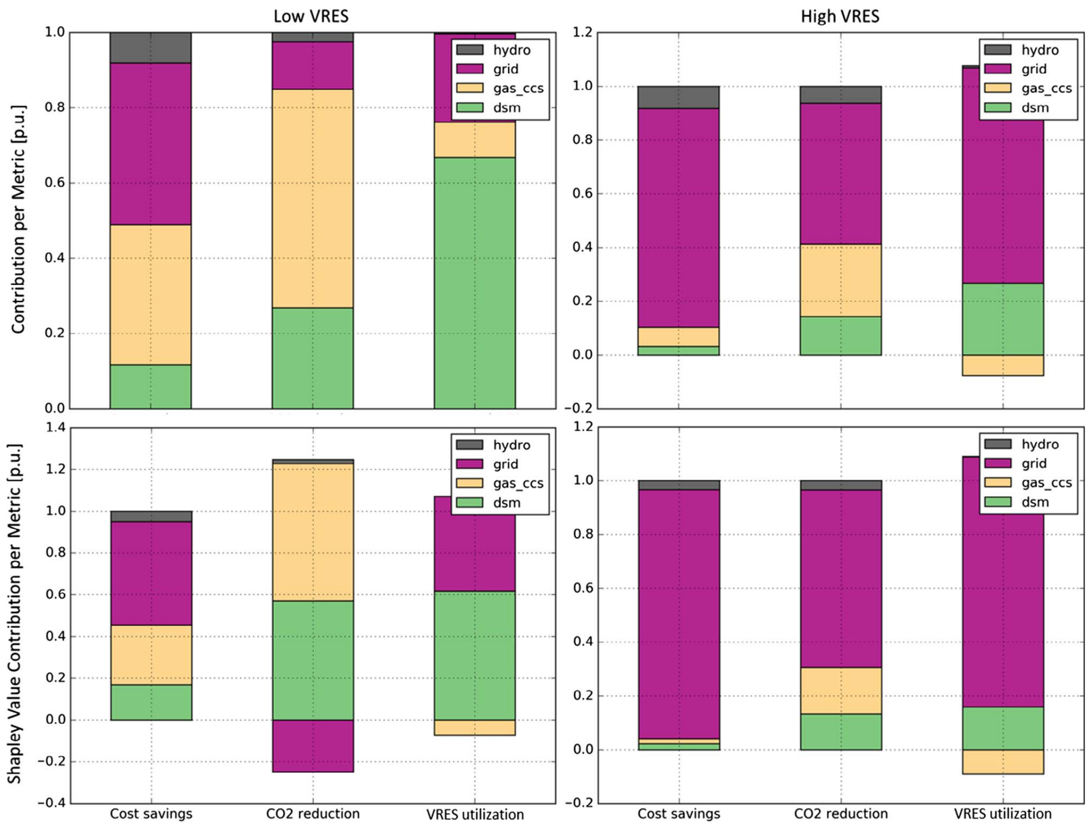

Fig. 4. Relative benefit contribution to the system in terms of cost savings, reduced CO_2 emissions, and increased utilization of renewable supply (reduced curtailment). The upper two plots shows the implicit value added by each technology option (traditional approach), while the lower two plots shows the value added for a range of possible deployment sequences (Shapley Value). Both for low- (left) and high (right) levels of VRES.

hours with very high wind- and solar feed-in, in combination with low demand).

4.4. Aggregate contribution to system benefits

From previous subsections, we know that grid contributes the most to operational cost savings at system level, due to its facilitation for other flexibility providers and its positive correlations with increasing shares of VRES. But what about its impact on CO_2 emissions and utilization of power generation from VRES? The upper part of Fig. 4 shows the added value for all the aforementioned metrics, as a result of hydro, grid, gas CCS, and DSM. Again, the left part represents low shares of VRES while the right part of the figure depicts the case with high shares of VRES. As expected for the high VRES case, the value added by grid expansion increases significantly relative to its competing alternatives, not only for operational cost savings, but also in terms of reduced emissions and increased utilization of VRES.

Gas CCS seems to provide a larger fraction of benefits at low levels of renewables, probably due to its competitive marginal cost for peak generation. Moreover, it might even lead to decreased utilization of renewables in high VRES scenario since its occurrence in one region might lead to imports from another, where cheaper, fossil fueled generation supplies parts of the exchanged capacity (from e.g. coal).

The lower two plots in Fig. 4 shows the added value considering all possible sequences of technology deployment, i.e. the SV. For instance, X is deployed first, Y second, Z third, and R forth, where all four flexibility providers are to be placed into different orders in an equivalent arrangement as the four variables. This way of calculating a system contribution accounts for competitive advantages, which is particularly useful in cases where this is highly uncertain. Moreover, it implies that one could account for some uncertainty without relying on any sophisticated, stochastic optimization programs, although a combination would probably generate more insights and knowledge.

With the SV results in mind, one could argue that grid is even more competitive with respect to most of the considered metrics for high shares of VRES, no matter which technology gets deployed at what time. For instance, if DSM is found profitable at an early stage, grid would still prove beneficial despite its disadvantage in terms of longer lead time. However, the added value of grid is harder to distinguish between traditional- (upper plots) and the SV approach (lower plots) for low shares of VRES (left part of Fig. 4), meaning that the competitive advantage is less significant for a future with low shares of VRES. Table 1 summarize the main difference between the SV- and traditional allocation for the low VRES scenario, where positive numbers implies that SV values a given technology more than the traditional approach.

An interesting observation from Table 1 is that, when considering all possible sequences, grid expansion might actually yield increased CO_2 emissions, on average. For this case, it seems that coal units achieve higher utilization when, for instance, gas CCS is deployed at an earlier stage than grid since the marginal flexibility provider (gas) has a higher marginal cost than coal. In other words, more grid allows for more coal export.

Table 1
The difference between the traditional approach and the Shapley Value in Fig. 4, measured in % deviation with respect to the traditional approach. A positive number would imply that the Shapley Value suggests a higher level of contribution from a particular flexibility provider. All numbers are based on the Low VRES case.

	DSM (%)	Gas CCS (%)	Grid (%)	Hydropower (%)
Cost savings	5.13	−8.42	6.34	−3.06
CO_2 reductions	20.26	7.51	−27.41	−0.36
VRES utilization	−4.91	−16.63	21.77	−0.23

Again, from Fig. 4 and Table 1, we see that gas CCS is very sensitive to market characteristics although it can contribute with significant value in some cases. Considering the possibility that other flexibility options might be deployed, gas CCS seems less attractive due to risk of being on the margin of the market clearing—potentially leading to stranded investments.

4.5. Discussion

Note that our goal is not to provide a detailed analysis of different flexibility providers, but rather present a framework for how it can be done. The results demonstrate that insights could be gained regarding the geographical demand for different flexibility technologies, their contribution to system benefits, and a benchmark for their contributions considering uncertainty in sequence of deployment (the SV). These insights could be useful for analysts and policy makers for identifying robust investments and energy policies.

Although the analysis relies on simplifications in operational details it does, however, reproduce similar observations found in the existing literature. For instance, grid expansion is shown to be the most prominent option due to its facilitation for increased availability of spatial flexibility, and consequently temporal flexibility from other providers that are geographically spread. In turn, this yields a positive impact on utilization of VRES and, through a more cost-efficient operation, also system cost savings. Moreover, by exploiting the properties of the SV, we can augment to the claim of grid being the most robust flexibility provider.

5. Conclusion

This paper presents an alternative way to perform an engineering-economic analysis of power system flexibility over a range of variable renewable energy source (VRES) capacity levels, ranging from 0% to 100% of the 2030 scenario "Vision 4" by ENTSO-E. The use of a fictive thermal unit allow us to approximate availability of both capacity and yearly energy inflow over this range of VRES capacities, yielding more reliable analyses for comparison. We evaluate all scenarios with a generation and transmission expansion planning (GTEP) model in order to assess individual, and combinations of, flexibility providers such as Demand Side Management (DSM), Gas CCS, Hydropower, and high-voltage cross-border transmission grid (Interconnectors).

We demonstrate our results with a North Sea Offshore Grid case study, discussing the geographical distribution of flexibility needs both

Table A.2
Notations for the generation and transmission expansion planning model.

Sets		
	$n \in N$	nodes
	$i \in G$	generators
	$b \in B$	branches
	$l \in L$	loads, demand, consumers
	$t \in T$	time steps, hour
	$i \in G_n, l \in L_n$	generators/load at node n
	$n \in B_n^{in}, B_n^{out}$	branch in/out at node n
Parameters		
	a, ω_t	factors for annuity and samplesize hour t [h]
	$VOLL$	value of lost load (cost of load shedding) [€/MW h]
	MC_i	marginal cost of generation, generator i [€/MW h]
	CO_{2_i}	CO_2 emission costs, generator i [€/MW h]
	D_{lt}	demand at load l, hour t [MW]
	C_b^{fix}, C_b^{var}	fixed- and variable capital costs, branch b [€, €/MW]
	B, B^d, B^{dp}	branch mobilization, fixed- and variable cost [€,€/km, €/km MW]
	CS_b, CS_b^p	onshore/offshore switchgear (fixed and variable cost), branch b [€,€/MW]
	CX_i	capital cost for generator capacity, generator i [€/MW]
	CZ_n	onshore/offshore node costs (e.g. platform costs), node n [€]
	P_i^{min}, P_i^e	minimum and maximum existing generation capacity, generator i [MW]
	γ_{it}	factor for available generator capacity, generator i, hour t
	$P_b^e, P_b^{n,max}$	existing and maximum new branch capacity, branch b [MW]
	D_b	distance/length, branch b [km]
	l_b	transmission losses (fixed + variable w.r.t. distance), branch b
	E_i	yearly disposable energy (e.g. energy storage), generator i [MW h]
	M	a sufficiently large number
Primal variables		
	IC, OC	investment- and operational costs [€]
	y_b^{num}	number of new transmission lines/cables, branch b
	y_b^{cap}	new transmission capacity, branch b [MW]
	z_n	new platform/station, node n
	x_i	new generation capacity, generator i [MW]
	g_{it}	power generation dispatch, generator i, hour t [MW]
	f_{bt}	power flow, branch b, hour t [MW]
	s_{nt}	load shedding, node n, hour t [MW]

by capacity allocation to individual countries and by capacity within each country. That is, how much DSM is deployed in country X, and at what share does DSM represent the capacity mix within country X. This allows us to assess where different types of flexibility options are most cost efficient.

In addition, we quantify the marginal value of each flexibility alternative in terms of operational cost savings (€/MW). We ignore investment costs, meaning that the resulting values can be regarded as break-even thresholds. Moreover, the relative impact on operational cost savings, reduced CO_2 emissions, and increased utilization of power generation from VRES are illustrated in relative terms, for each alternative. We apply the Shapley Value from cooperative game theory in order to analyze the latter impact incorporating all possible deployment sequences. The Shapley Value does, for instance, implicitly account for the disadvantages of long lead time or the advantage of learning rate, e.g. the long lead time of grid investments and future cost-efficient DSM solutions, respectively.

The authors acknowledge the low level of details in the model used to quantify those benefits, which is why this work can be viewed as a generic framework to do equivalent analyses. This framework could easily be reproduced with more detailed planning models or market simulators, incorporating a proper representation of unit commitment, storage, and load flow equations. An interesting extension of this work could be to use a stochastic model to calculate characteristic functions for the Shapley Value, and compare this with the deterministic one. This could give an idea about the level of uncertainty that Shapley Value mange to incorporate in its combinatorial calculation scheme.

Other interesting extensions includes dynamic investment models. In this paper, we incorporate different sequences for deployment but ignore the discounted monetary value with respect to the time between different deployments. Moreover, marginal contributions calculated with SV are based on bulky capacity investments. This means that each technology is not deployed partially, but in full scale determined by the expansion model. With Aumann-Shapley (AS), it is possible to capture the marginal contribution at fractional levels. Hence a comparison of SV and AS would be interesting both from a computational perspective and in terms of the resulting allocations.

Acknowledgment

The expansion planning model used for this work is called PowerGIM. PowerGIM is a open-source model under the market simulator PowerGAMA [38], which can be downloaded at bitbucket.org. The authors would like to thank the developers behind PYOMO [49], in addition to Gurobi Optimization and anonymous referees for constructive feedback.

Appendix A. Notations for GTEP model (PowerGIM)

See Table A.2.

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Paper G

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Multistage grid investments incorporating uncertainty in offshore wind development

Martin Kristiansen[a,*], Harald G. Svendsen[b], Magnus Korpås[a], Stein-Erik Fleten[c]

[a]*Department of Electric Power Engineering, NTNU, Trondheim, Norway*
[b]*SINTEF Energy Research, Trondheim, Norway*
[c]*Department of Industrial Economics and Technology Management, NTNU, Trondheim, Norway*

Abstract

Representation of uncertainty in long-term transmission expansion planning (TEP) models has become increasingly important as many power systems are exposed to significant technological changes induced by top-down climate and energy targets. The objective with this paper is to incorporate uncertainty regarding future offshore wind deployment and allow two investment stages for grid expansion, where the second stage provides valuable flexibility for a system planner. A stochastic two-stage mixed-integer linear program is used for this purpose applied to a case study of the North Sea Offshore Grid (NSOG). With the given data and assumptions, we show that the system planner can gain maximum €1.72 bn (0.40 %) in terms of cost savings under perfect information about the wind deployment. The expected cost savings for a more forward-looking system planner using a stochastic program is €22.30 m (0.0052 %), in comparison with the best deterministic approach. Moreover, we show that if the planner can postpone its investment decision with five years an expected cost saving of €22.41 m would arise.

Keywords:
Transmission Expansion Planning, North Sea, Offshore Wind, Uncertainty, Flexibility

1. Introduction

1.1. Increasing system uncertainty

Many power systems are exposed to large-scale integration of non-dispatchable technologies the coming decades [1], which demands more flexibility in order to distribute, consume, or store variable levels of power feed-in. An adequate grid infrastructure can provide the system with more spatial flexibility, i.e. to distribute power surplus over a larger geographical area, which in turn connects non-dispatchable generation to distant load centers and potential energy storage (temporal flexibility) [2,3]. Moreover, one could also benefit from spatial smoothing effects due to

* Corresponding author. Tel.: +47 934-26-649
E-mail address: martin.kristiansen@ntnu.no

synergistic effects in variable renewable energy source (VRES) inflow, such as wind speed and/or solar irradiation, making grid reinforcements even more beneficial [4,5]. However, grid investments for this purpose are exposed to uncertainty regarding the system characteristics under which it will cover its costs.

As for technological changes on the supply side, there is a particularly high potential for offshore wind power in the North Sea area. The North Sea Offshore Grid (NSOG) has therefore been identified by the EU Commission as one of the strategic trans-European energy infrastructure priorities in the EU Regulation No 347/2013, as it potentially serves the twofold purpose of integrating renewable power generation and cross-border trading. According to ENTSO-E's ten-year network development plan (TYNDP) [6] it is already planned €105-120 bn investments within 2030 for trans-European projects.

The lumpiness and size of multinational interconnectors can have a significant material impact on expected market prices [7]. More cross-border trading has been an important research topic since it bring along considerable market impacts not only on prices and welfare [8], but also through a re-dispatch of fossil fueled generators (CO2 emissions) and regional investments (renewable share) [9].

The NSOG is surrounded by multiple countries such as Norway (NO), Denmark (DK), Germany (DE), Netherlands (NL), Belgium (BE), and Great Britain (GB). Those countries have to decide upon lumpy, large-scale investments that are expected to be in operation over a long lifetime. The investments are naturally dependent on the future power system and its generation mix. Hence, we believe that investments of this size and impact should be studied in more detail with tools that incorporate uncertainty. A forward-looking system planner would benefit from this with an investment strategy that is hedged against future scenarios for e.g. offshore wind capacity/deployment, which is a highly uncertain parameter on those time scales. The next subsection will give insight to the current status in this respect.

1.2. Incorporating uncertainty in long-term TEP models

TEP has been a widely studied problem the last decade and its complexity has induced more advancement in operations research, making it possible to advance even more [10]. In a recent literature review [11] they dive into TEP studies related to the NSOG and finds, among other things, a lack of research that incorporates uncertainty. The most qualified findings on this topic, that the authors are aware of, comprise of a strategic planning approach using a minimum-regret analysis [12]. Munoz et al. quantifies the importance of including uncertainty into planning models for the Western Electricity Coordinating Council (WECC) system [9], in comparison with traditional planning methods.

Uncertainty in fuel prices, technology costs, deployment timing, and policies has gained more attention for planning models. TEP models that incorporate uncertainty include [13] and [2], and in combination with generation expansion planning (GEP) [14] and [5] that quantifies the value of accounting for uncertainty, and [15] which discuss more the computational aspects of stochastic programs. One occurring program setup, except in [14] and [2], is that they all consider an investor making one investment at the beginning of the analysis period, and disregards the opportunity to postpone.

In this article we present a forward-looking transmission system planner as a two-stage program co-optimizing investments and operation, leaving the investor with the option to postpone investments in order to learn more about the offshore wind deployment, which is assumed to be the uncertain parameter. The results illustrates topological effects for the NSOG in year 2030 and 2035, in contrast to [14] and [2] that focus more on numerical results for a case study of Great Britain and IEEE-RTS, respectively. Hence, to our knowledge, the main contributions from this article is i) a stochastic program for offshore TEP, and ii) a comparative topological study with respect to deterministic solutions of the same problem providing metrics about iii) the value of stochastic solution (VSS), expected value of perfect information (EVPI), and real option value (ROV) of the flexibility to postpone investments.

The remaining part of this article is structured as follows; Section 2 gives an introduction to the model, preprocessed data and timeline for the model and its potential application. Section 3 gives a short overview of the case study scenarios before the final results. Results from a deterministic TEP approach is first presented, followed by a stochastic solution that incorporates uncertainty in offshore wind deployment. The relevant findings are finally concluded in Section 4.

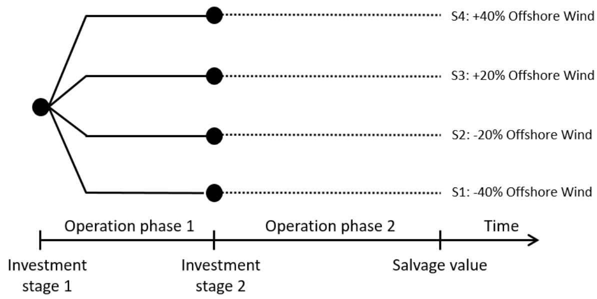

Fig. 1. Illustration of the timeline and uncertainty in offshore wind capacity deployment. Investments in grid capacity are made before (stage 1) and after (stage 2) the final wind capacity is revealed, calculated as +/- 40% of base case (ENTSO-E Vision 4 year 2030).

2. Methodology

To carry out the evaluation of infrastructure investments under uncertainty, we present a new two-stage stochastic transmission expansion planning (TEP) tool called PowerGIM. The model is a combination of an investment model [3,16] and a market simulator [17]. Initial investment decisions are made in the first stage for offshore infrastructure capacity (stage 1), followed by five years of operation (phase 1), corrective investment decisions (stage 2) after uncertainty is revealed regarding offshore wind development. The final system is then operated over the rest of the economic lifetime, e.g. 25 additional years, and any salvage values are discounted back to year 0. The timeline of this aforementioned scenario tree is also depicted in Figure 1.

As a benchmark to evaluate the expected value of this approach, an deterministic equivalent is solved for one scenario at a time with 100% probability. I.e. results that are based on four deterministic scenarios or one expected value scenario when assuming a symmetric probability distribution.

2.1. Model description

The TEP model co-optimizes investment decisions and market operation in a power system consisting of several price areas (see Figure 2). Power flows are modelled as a transport model, since the NSOG is largely based on controllable HVDC links. A compact formulation of the stochastic two-stage MILP is given by Equations (1a) - (1c).

$$TC = \min_{x} c^T x + E_\xi[\min_{y(\omega)} q^T y(\omega)] \tag{1a}$$

s.t.

$$Ax \leq b \tag{1b}$$

$$T(\omega)x + Wy(\omega) \leq h(\omega), \quad \forall \omega \in \Omega \tag{1c}$$

$$x = (x_1, x_2) \geq 0, x_1 \in \mathbb{Z}^+, y(\omega) = (y_1(\omega), y_2(\omega), y_3(\omega)) \geq 0, y_1(\omega) \in \mathbb{Z}^+ \quad \forall \omega \in \Omega$$

The objective function (1a) is divided into two stages; first the costs related to infrastructure investments, x, and second, the expected costs related to market operations in phase one, $y_1(\omega)$, compensating infrastructure investments, $y_2(\omega)$, and market operation of the remaining analysis period, $y_3(\omega)$, dependent on a discrete set of scenarios, Ω. One could discuss whether a set of discrete scenarios is realistic, but for our practical application it is considered as a good approximation. However, in this study we choose a wide range of possible offshore wind capacities between stage one and stage two, ranging from 60 – 140% of the initial capacity that the system planner sees when making the first investments (ENTSO-E Vision 4) [6]. Note that the infrastructure investments consists of both block-capacity (integer variables x_1) and variable capacity (continuous variables x_2).

There is a five year time period between the two investment stages, i.e. phase one in 1, meaning that the cost vectors has to be discounted accordingly (5%) in addition to calculating any salvage value for assets with remaining economic lifetime (30 years).

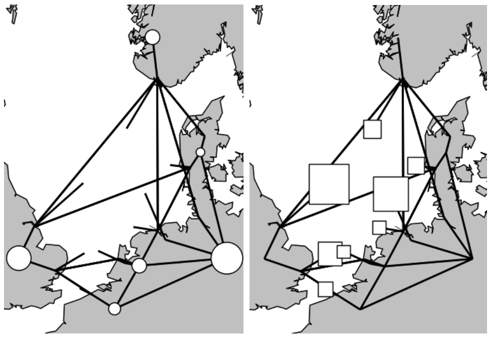

Fig. 2. Base case - NSOG for year 2030 including both existing and planned interconnections. Offshore wind connections are also included with higher transfer capacity than the installed offshore wind capacity, in order to narrow the scope to a pure interconnection analysis. Relative peak load (left plot; circles) and relative offshore wind capacity (right plot; squares).

The vectors and matrices c, b, and A in (1a) and (1b) are associated with the first stage variables, i.e. investment in grid infrastructure. The cost vector c is for both fixed and variable node- and branch costs, although node costs are not relevant for this particular case study. Vector b restricts the first stage variables, e.g. by maximum allowed capacity per investment block (e.g. 1000 MW per branch), and A is the corresponding coefficient matrix to those investment constraints.

The second stage parameters depend on the realization of $\omega \in \Omega$, i.e. the parameters are not quantified before uncertainty in wind deployment is revealed. The cost vector q is equivalent to c, but it includes marginal costs of generation, CO2 costs (45 €/tonCO2), and value of lost load (VOLL) which is multiplied with market operation in phase one and two, and discounted according to the timeline depicted in Figure 1.

The right-hand-side vector in (1c), $h(\omega)$, restricts decision variables in scenario ω, i.e. relevant restrictions on market dispatch and second stage investments. The *transition matrix*, $T(\omega)$, is associated with first stage variables and can be interpreted in the right hand side restriction together with $h(\omega)$. The transition matrix contains scenario and/or time-dependent data that effects operation in second stage. The recourse matrix, W, is considered fixed in this model since the coefficients in the matrix is independent on the realization of ω.

2.2. Preprocessed input data

We use time series data from the numerical weather prediction tool COSMO EU [18], with a sophisticated modelling routine simulating a meshed data grid with a point to point resolution of 7x7km in Europe. The resulting 665x657 geographical data nodes are then used to collect data for wind speeds and solar irradiation, which in turn is simulated into full-year power-output profiles. It is shown in [3] that COSMO-EU performs well for TEP applications, in comparison with numerical weather data with lower spatial and temporal resolution. Also, one could collect data from geographical coordinates that has no historical, measured data, e.g. wind speeds offshore.

The curse of dimensionality for this stochastic program makes it necessary to reduce the size of time series used to describe non-dispatchable generation and load. Previous literature, such as e.g. [16], argues that 200 time steps should give stable objective values for a TEP model. However, this paper relies on $8760/2^7 = 68$ time steps using the k-means clustering approach [19]. Since the scope of this paper is a comparison of different solution approaches, the sample size is assumed to be sufficient enough to capture a variety of possible flow patterns induced by variation in non-dispatchable generation and load.

The cost data for branch investments are calculated beforehand based on distance and whether a connecting node is onshore or offshore. The distinction between onshore and offshore nodes are important in order to reflect correct costs for transformers and/or power electronics needed for transmitting AC or HVDC. It is recommended to consult [16] for more details around the cost functions.

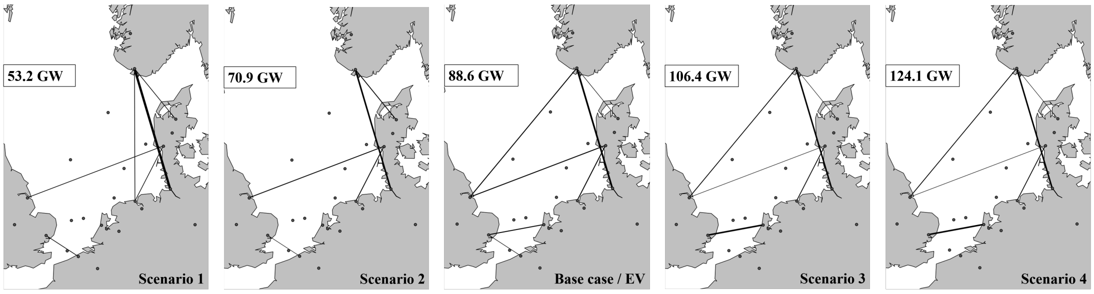

Fig. 3. Deterministic solutions with additional capacity (relative thickness of plotted lines). All first stage investments with perfect foresight about offshore wind deployment. Offshore wind capacity and scenario number are given in the figure, including the base case (EV) scenario.

2.3. Timeline and scenarios

The analysis starts in year 2030 with an economic lifetime of 30 years, ending in year 2060. ENTSO-E Vision 4 [6] is given as data input for year 2030, in addition to already planned and existing infrastructure, and investment decisions regarding grid capacity has to be made (stage 1). After 5 years of operation under those conditions, the offshore wind capacity turns out to deviate from the initial capacity with +/- 40%. Based on this new information, corrective grid investments can be made in year 2035 (stage 2) as depicted in Figure 1.

3. Case Study

The NSOG is considered as a case study and four different solution methods are considered; i) deterministic wait-and-see decisions based on the expected value scenario, ii), deterministic wait-and-see decisions based on each of the four input scenarios, iii), investment decisions made with a here-and-now stochastic program, and iv), investment decisions made in two stages, year 2030 and 2035, with a stochastic program considering four different scenarios that evolve after the first stage. Based on those results, we can quantify the expected value of perfect information (EVPI), value of stochastic solution (VSS), and real option value (ROV) of postponing investments.

Both existing and planned cables within year 2030 are included. In addition, offshore wind nodes (as depicted in e.g. Figure 3) are excluded as variables since we assume that the wind capacity and connections are already in place. Hence, the resulting case study has already a strong grid connection with offshore wind capacity. Additional capacity investments are on the margin and the focus is narrowed down to interconnector investments (cross-border links), only. Meaning that we do not optimize the full offshore grid, only additional capacities at existing (in 2030) branches.

3.1. Deterministic solution

Figure 3 shows the deterministic results for the four different offshore wind capacity scenarios, including the expected value solution which is equal to the initial data input (ENTSO-E Vision 4). As more offshore wind capacity is introduced to the system, the system planner choose to strengthen the transmission capacity to GB, from both NO (2000 MW) and NL (4000 MW). Flexible hydropower in NO is valuable in order to utilize low-cost generation capacity at both the continent and in GB more efficiently. Other transmission links remain more or less stable between the different solutions. Table 1 shows the investment costs occurring in each deterministic scenario, ranging from 8850 MW to 13850 MW new transmission capacity (€12.66-19.19 bn).

A system planner that only considers a scenario analysis would probably argue that investments that occur in all scenarios are robust (robustness analysis). In such a case, interconnectors between NO-DE, NO-DK, DK-NL, and GB-DK would score highest under those criteria.

A second approach, in addition to the robustness analysis, is to use the expected wind capacity as given (EV plot in Figure 3). From the figure we see that the expected value solution also contains any decisions that would result from a robustness analysis. If the system planner decides to use all investments from the expected value solution, and uncertainty is revealed, the costs occurring in each of the scenarios would be higher than for each representative

Table 1. Total costs and investment costs when fixing the investment decisions from the EV solution and exposing it to scenario 1 (low wind) - 4 (high wind). Compared with perfect foresight wait-and-see the value of perfect information is quantified. All values are given in bn€.

	S1	S2	S3	S4	Expected value
EV solution	487.74	449.22	400.80	384.99	430.69
→ Investment costs	19.86	19.86	19.86	19.86	19.86
Deterministic solution	484.70	447.70	400.11	383.29	428.95
→ Investment costs	12.66	14.85	19.19	19.19	19.86
Value of information	3.04	1.53	0.68	1.70	1.74

deterministic solutions (perfect foresight) as shown in Table 1. I.e., the deviation would represent the value of perfect information without any stochastic program available. Note that the total costs of the expected value scenario is lower, amounting to €421.21 bn, referred to expected value (EV) solution. The expected costs of using this EV strategy is referred to as EEV, which can be seen from Table 1 at €430.69 bn. The increase in costs reflects the costs of uncertainty.

Note that the EV investment cost is higher than all deterministic scenarios, even those with higher wind capacity (scenario 3 and 4), but the accumulated new capacity is the same; 13850 MW. Instead of having 4000 MW between NL-GB, the system planner allocates 1000 MW to DK-GB and 1000 MW to BE-GB of those 4000 MW at a higher investment costs but at lower operational costs, harvesting more offshore wind from the northern part of the continent (cable investments shifts north between GB and the continent).

The EEV represents the expected costs of using a strategy that copes with uncertainty in a deterministic case. Hence, we could use this metric to quantify the gap to a more sophisticated approach that even hedges some outcomes (minimize the cost that occur on average in all scenarios); the stochastic solution. This would be the expected cost of ignoring uncertainty, also known as the value of a stochastic solution (VSS). I.e. the value of using a stochastic program instead of a deterministic one, given the number of scenarios and probability distribution used. This is, however, only an estimate.

3.2. Stochastic solution: One investment stage

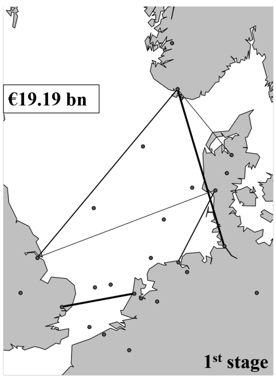

Fig. 4. Two-stage stochastic solution when only considering one investment stage (year 2030). Investment cost is given in the figure.

With a classical two-stage formulation, i.e. without second investment opportunity, the first stage investments are directly followed by market operation under four different scenarios. In this case you could hedge against future market outcomes, but you can not postpone investment decisions to eliminate some risk (option value). Figure 4 shows the topological result of an investment portfolio made by such a program.

The first thing to note is that this portfolio covers almost all deterministic outcomes, except NO-NL and GB-BE. Moreover, it deviates from a robustness analysis with NO-GB and GB-NL. The key take away from the topological results is the hedging effect, although it is hard to see the underlying market impact on operational costs. The stochastic

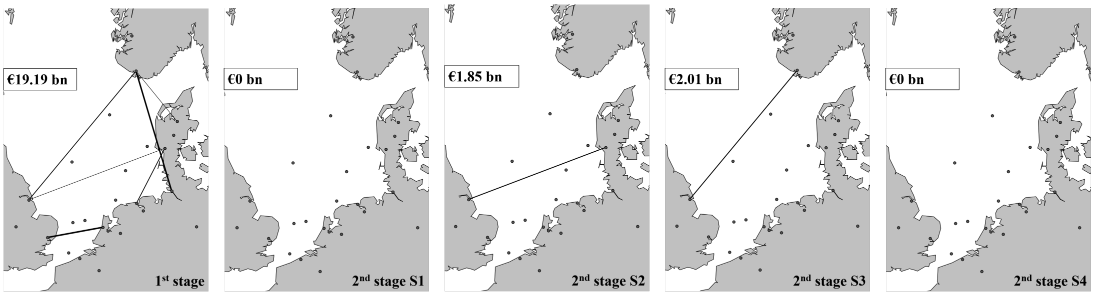

Fig. 5. Multi-stage stochastic program solutions. The first stage investments in the most-left figure, followed by second stage investments ranging from scenario 1-4. The system planner has the option to postpone investments, typically the ones that only occur in particular scenarios. Investment costs are given in the figure.

investment strategy ensures that the system has enough grid capacity to cope with the most ambitious wind scenarios. Recall that the base case costs €421.21 bn at €19.86 bn investment cost, and if one compare this with the individual scenarios one would see that there is a larger gain in terms of cost savings moving toward the high wind scenarios (rather than disregarding investments at a higher total cost).

A decision maker's best available tool to incorporate as much information as possible is in our case a stochastic program. Hence, the maximum amount she is willing to pay for perfect information must be the expected cost savings between this option and perfect foresight. The expected value of the deterministic wait-and-see solutions, is subtracted from the more costly stochastic solution, representing the EVPI. The EVPI is €1.72 bn (0.40% of the stochastic total costs).

Moreover, the VSS can be calculated by looking at the outcomes of using the expected value strategy listed in Table 1, which represent the expected value of using the expected scenario (EEV). This is a more costly approach than the stochastic solution, and the deviation between them is the VSS. The VSS in this case amounts to €22.30 m (0.0052%), meaning that this is the expected cost savings of our hedging strategy.

3.3. Stochastic solution: Two investment stages

By allowing multi-stage investment decisions the system planner might find it beneficial to withhold investments in order to learn about uncertain data. The deviation from a one step here-and-now decision represents the option value of postponing an investment.

Figure 5 shows the first stage investments (left plot) and the subsequent second stage investments from scenario 1 (low wind) to 4 (high wind). The forward-looking system planner finds it beneficial to postpone some investments, in order to eliminate risk of stranded investments or costly market operation. 1000 MW are added in both scenario 2 and 3 at a cost of €1.85 bn and €2.01 bn, respectively. Comparing with the deterministic EV strategy, we see that the second stage investments from Figure 5 represents the outliers in the deterministic solutions, i.e. they only arise in one or two scenarios. E.g. in scenario 3 additional 2000 MW is added to NO-GB in the deterministic case, but since the other scenarios does not yield the same, a forward-looking system planner would prefer to reduce the first stage investment to from 2000 MW to 1000 MW and wait to see whether scenario 3 occurs, or not.

Note that there are no additional investment in the high offshore wind scenario, i.e. the most-right plot in Figure 5, which is a bit counter intuitive since one would assume that more grid is needed in order to distribute the wind generation. However, it seems to be caused by the fact that the relative proportion of additional offshore wind capacity cancel out some of the price deviations between GB and the continent (including NO), leaving the grid investments that are on the margin, less attractive. Demand for flexible hydropower in NO is shifted to the continent, where the transmission capacity is sufficiently high from the first stage investments.

The total expected investment cost is higher than in the previous cases, amounting to €20.16 bn. This means that the flexibility to postpone reduce the total costs, even with more investments. By comparing the total costs with the results from Subsection 3.2, i.e. the solution with one investment opportunity, the ROV amounts to €23.41 m

(0.0054%). This is equivalent to the price a system planner would be willing to pay in order to have the option to exercise the second stage investments after five years of operation. Another way to look at it is the value of flexibility.

3.4. Discussion

First, we used a deterministic program to evaluate which investment strategies that copes the best with uncertainty in offshore wind deployment. One could either solve the scenarios independently and do a robustness analysis, or use the expected scenario to get one unique strategy, instead of four. We saw already then that trying to incorporate uncertainty into one investment strategy came at a cost, since the true total costs of this strategy had to be evaluated under the realization of all scenario (the EEV solution).

The stochastic program allowed us the further quantify the EVPI, VSS, and ROV. One occurring observation is that a forward-looking system planner tends to invest in more capacity than in the naive deterministic cases, where the excess capacity represents a hedge against future scenarios. This hedge is justified by the VSS amounting to €22.30 m. Moreover, the system planner is willing to pay €23.41 m (the ROV) in order to have the option to postpone investment decisions with five years. Note that the case study already contains strong grid connections in the base case, and that we only consider uncertainty in offshore wind capacity, which together limits the aforementioned metrics.

"More is better" would be the key take-away from these results, due to the fact that a forward-looking system planner is willing to invest more in order to both enhance its flexibility, reduce total costs, and eliminate risk, with respect to uncertain offshore wind deployment.

4. Conclusion

This paper presents a stochastic program for offshore transmission expansion planning (TEP) with one and two investment stages, respectively. A deterministic program of the equivalent problem is used in order to quantify metrics concerning the expected value of perfect information (EVPI), value of stochastic solution (VSS), and real option value (ROV).

The models are applied to a case study of the North Sea Offshore Grid (NSOG) with ENTSO-E's "European Green Revolution" scenario (Vision 4) for year 2030. Existing and planned interconnections in the NSOG are given exogenous, while additional grid investments are given as "wait-and-see" (deterministic) and "here-and-now" (stochastic) solutions. Moreover, a forward-looking investor is presented by allowing two investment stages with a five year gap in order to postpone less robust investment opportunities as uncertainty about offshore wind capacity evolves.

There are a few assumptions and weaknesses limiting the validity of the results obtained in the comparison. Note that we do not consider any time delays of the transmission investments, meaning that the new assets are in operation right after the decision has been made. Moreover, the scenarios that are used in this study are simply based on four different exogenous scenarios and not any well-established scenario reduction/generation technique. The set of scenarios could include more than just offshore wind development. In addition to the aforementioned limitations, future research could include a bi-level game with responsive generation investments in the second stage, which is implementable within the same framework presented in this paper. Also, more frequent decision stages would give a better intuition for the ROV assessment.

Results from the work presented in this paper does, however, provide the intuition behind the key decision support tools available for TEP that copes with uncertainty. Topological illustrations are provided and metrics quantified in order to show that the different approaches yields different investment strategies. Keep in mind that the base case represents a strong grid infrastructure for year 2030, and any additional investments would therefore be on the margin, which limits the metrics calculated in this study.

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Paper H

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Paper H

A Mechanism for Allocating Benefits and Costs from Transmission Interconnections under Cooperation: A Case Study of the North Sea Offshore Grid

Martin Kristiansen[*1], *Francisco D. Muñoz*[**], *Shmuel Oren*[***], *Magnus Korpås*[*]

ABSTRACT

We propose a generic mechanism for allocating the benefits and costs that result from the development of international transmission interconnections under a cooperative agreement. The mechanism is based on a planning model that considers generation investments as a response to transmission developments, and the Shapley Value from cooperative game theory. This method provides a unique allocation of benefits and costs considering each country's average incremental contribution to the cooperative agreement. The allocation satisfies an axiomatic definition of fairness. We demonstrate our results for three planned transmission interconnections in the North Sea and show that the proposed mechanism can be used as a basis for defining a set of Power Purchase Agreements among countries. This achieves the desired final distribution of economic benefits and costs from transmission interconnections as countries trade power over time. We also show that, in this case, the proposed allocation is stable.

Keywords: Cooperative game theory, Cost-benefit allocation, Transmission expansion planning
JEL:

1. INTRODUCTION

Many countries in the European Union (EU) plan to incorporate large shares of electricity supply from renewable energy technologies—particularly solar and wind power—in the coming decades (ECF, 2011). Unlike conventional generation technologies, the variability and unpredictability of renewable resources result in higher needs for flexibility in order to maintain the reliability of a power system (Denholm and Hand, 2011). One source of flexibility is the possibility of balancing distinct generation resources and demand across large geographical areas through high-voltage transmission lines (Munoz et al., 2012; Konstantelos and Strbac, 2015). Distant wind farms, for instance, can present synergistic effects by geographic diversification (Hasche, 2010), which can reduce the need for other sources of flexibility such as storage and fast-ramping generation units.

Transmission interconnections are one way to capture the benefits from the spatial diversification of resources. They can also result in economic and environmental benefits from avoided fuel costs, postponement of local generation investments and transmission reinforcements, and reductions in aggregate carbon emissions due to power exchange (UN, 2006). For these reasons, the EU Commission has identified the North Sea Offshore Grid (NSOG) as one of the strategic trans-European energy infrastructure priorities in the EU Regulation No 347/2013 (EUL, 2013). In a recent study,

[*]Department of Electric Power Engineering, Norwegian University of Science and Technology, Trondheim, Norway. Corresponding author[1]. E-mail: martin.kristiansen@ntnu.no.
[**]Facultad de Ingeniería y Ciencias, Universidad Adolfo Ibáñez, Santiago, Chile.
[***]Department of Industrial Engineering and Operations Research, University of California Berkeley, CA, USA.

Strbac et al. (2014) estimate that the aggregate economic benefits from the NSOG are between €8bn and €40bn depending on the level of coordination that participant countries will achieve.

In practice, achieving a cost-effective portfolio of transmission developments for a NSOG from a system-wide perspective can be quite challenging since there is no centralized authority with the legal power to force countries to accept the proposed plan. The latest development plan by the European Network of Transmission System Operators for Electricity (ENTSO-E), an organization that promotes cooperation across Europe's Transmission System Operators (TSOs), states that nearly €150bn worth of investments will be needed for pan-European infrastructure expansions in order to meet projections of demand and environmental targets at minimum cost by year 2030 (ENTSO-E, 2016). However, it is not clear how many of the proposed projects are actually supported by individual countries in the region.

A unique feature of international transmission interconnections is that they can be unilaterally vetoed by a country at one end of the proposed project if it considers that it will receive an unfairly low fraction of the net economic benefits that result from the project (i.e., net of imports, exports, local changes in electricity prices and carbon emissions, and the allocated portion of congestion rents[1] and investment cost of the transmission line). We refer to these as *host countries*. Moreover, *third-party countries*, which are part of the existing interconnected transmission grid but will not host any of the proposed lines, might also be affected by large grid developments elsewhere in the network. Ignoring the impacts on third-party countries could result in political tension among members of the interconnected system or failure to realize the full benefits of a highly interconnected grid. For instance, cost-bearing countries could have difficulties in achieving an agreement due to free-riding issues if a third-party country that receives positive net benefits from new transmission projects is not considered in the negotiations. On the other hand, a third-party country that is negatively affected by new transmission projects might be able to pose credible threats to the overall system if it does not receive a compensation that is commensurate with its local economic losses. One possible threat is to arbitrarily reduce the degree of coordination in the hourly dispatch of local generating resources with the rest of the system, a measure that could increase costs in some neighboring regions. A third-party country could also refuse to provide a required amount of balancing services in a synchronized area and cause frequency deviations that could put the system stability of an entire interconnected region at risk.[2] Consequently, achieving all the economic benefits that would, ideally, result from international transmission interconnections might require more than just bilateral agreements between hosting countries. Building a broad consensus among all countries in a region to support transmission interconnections is, in fact, in the spirit of Regulation (EU) No 347/2013 (EUL, 2013).[3]

Failure to achieve an agreement to develop a cost-effective portfolio of transmission investments in the region can also have an impact in the location, size, and type of new investments in generating capacity (Sauma and Oren, 2006; Munoz et al., 2013, 2014). For instance, many of the proposed transmission projects in the NSOG are actually needed if countries have goals of harnessing the vast amount of onshore and offshore wind resources available in the North Sea (Konstantelos et al., 2017a; Gorenstein Dedecca et al., 2018). If these are not developed, it is likely that demand projections and environmental goals will be met with less efficient resources at a much higher cost

[1]Congestion rents are defined as the price difference times the power flow over a transmission asset.

[2]During early 2018, the entire Continental European Power System experienced a continuous frequency deviation as a consequence of a political conflict between Servia and Kosovo. The frequency deviation occurred because Servia refused to balance Kosovo's system during a shortage of power supply in the latter (ENTSO-E, 2018)

[3]Annex V in page 72 of EUL (2013) describes a series of principles for methodologies for harmonized energy system-wide cost-benefit analysis for projects of common interests in the EU. According to principle (10), *"(t)he (proposed) methodology shall define the analysis to be carried out, based on the relevant input data set, by determining the impacts with and without the project. The area for the analysis of an individual project shall cover all Member States and third-party countries, on whose territory the project shall be built, all directly neighboring Member States and all other Member States significantly impacted by the project." Furthermore, according to principle (11) "(t)he analysis shall identify the Member States on which the project has net positive impacts (beneficiaries) and those Member States on which the project has a net negative impact (cost bearers)" (EUL, 2013).*

(e.g., distributed rooftop solar PV in areas with low radiation instead of large-scale offshore wind farms in windy regions). Large transmission investments can also change electricity prices in a network and shift investments of any type of generation technology, including conventional power plants, from one country to another (Hogan, 2018). Finding a mechanism to support the development of cost-effective portfolios of transmission investments from a system-wide perspective is, therefore, just as important as identifying them in the first place under a central-planning paradigm as demonstrated by Grigoryeva et al. (2018) and Olmos et al. (2018) for the North-Western European and Spanish power systems, respectively.

In this article we present a mechanism for allocating the net economic benefits that result from international transmission interconnections among a group of countries that are willing to reach a cooperative agreement to support a cost-effective portfolio of transmission investments. Our approach is based on a planning model that considers generator's response to transmission investments in a competitive setting and the Shapley Value (SV) from cooperative game theory. One of the great advantages of this mechanism is that it provides a *fair* and unique allocation of benefits for all countries under the so called *grand coalition* based on the average incremental contribution from each country towards the cooperative agreement. This information can then be used to determine a set of side payments among countries that will be necessary to achieve the final allocation determined using the SV. Conveniently, this allocation satisfies an axiomatic definition of fairness.

We illustrate the proposed allocation method on a network that simulates power production and trade among six countries in the North Sea region in year 2030. We consider all the possible realizations (i.e., built or not built) of three offshore transmission projects that are planned in this region: the North Sea Link between Norway and Great Britain, the NordLink between Norway and Germany, and the Viking cable between Denmark and Great Britain (ENTSO-E, 2016). We apply the proposed mechanism to this case study and compare the difference between the ideal final allocation of benefits under the SV and two conventional allocation rules that allocate transmission costs and congestion rents among countries: 50/50 split and a proportional split with respect to estimated benefits from transmission upgrades. Assuming that interconnections will be initially funded through one of these conventional allocation rules, we determine the side payments needed to achieve the SV and define a set of Power Purchase Agreements (PPAs) that will achieve the desired distribution of benefits as countries trade power over time. We also verify that, in this case, the SV is in the core because the game is convex. This means that the SV allocation is not only fair but also stable since countries have no incentives to deviate from the grand cooperative agreement by forming smaller subcoalitions. Although stability is not a general result, the proposed mechanism can be helpful in supporting cost-efficient transmission interconnection projects.

We structure the rest of the paper as follows. In Section 2 we overview existing literature on transmission planning with a focus on centralized and cooperative mechanisms. In Section 3 we discuss the reasons for which it is unlikely that decentralized mechanisms will result in agreements to support a socially-optimal set of transmission interconnections. In Section 4 we use two simple examples to show how expanding the capacity of a congested transmission line could lead to asymmetric, or even negative, net benefits for some countries in an interconnected system. In Section 5 we describe the proposed methodology, including a high-level description of the planning model and the steps to compute the SV. In Section 6 we describe the case study and present our results. Finally, in Section 7 we conclude.

2. TRANSMISSION PLANNING AND COST ALLOCATION MECHANISMS IN CENTRALIZED AND COOPERATIVE SETTINGS

Transmission planning is an active area of study, particularly in the field of operations research. This is because finding a socially-optimal plan (e.g., the one that minimizes total system costs) from a set of candidate portfolios can be computationally challenging, even if all transmission investment decisions are made by a central authority (e.g., a national energy commission or a regulated transmission organization) (Latorre et al., 2003; Hemmati et al., 2013). Large transmission networks can have millions of possible investment combinations and finding the optimal one might sometimes require the use of sophisticated optimization algorithms in combination with high-performance computers (Munoz and Watson, 2015; Munoz et al., 2016). Also, in deregulated markets transmission investments can alter electricity prices and, consequently, incentives for investments in new generating capacity (Spyrou et al., 2017). Depending on the market structure, consideration of generator's response to transmission investments might require the use of equilibrium models that involve the implementation of non-trivial algorithms to find an optimal solution (Sauma and Oren, 2006; Pozo et al., 2013). Uncertainty of input parameters such as demand, fuel costs, and carbon prices can also complicate decision making (Munoz et al., 2014, 2015), particularly if planners are risk averse (Munoz et al., 2017).

Additionally, the siting process of new transmission lines can be difficult if voluntary negotiations with landowners to obtain easements on private property fail, or if local communities or interest groups do not approve the development of new infrastructure in a determined area (Ciupuliga and Cuppen, 2013; Bertsch et al., 2016). However, these conflicts do not always result in cancellation of transmission projects. In many jurisdictions, regional transmission organizations are granted the power of eminent domain to develop infrastructure that is deemed necessary when voluntary negotiations fail (Meidinger, 1980; Rossi, 2009). Consequently, broad approval of transmission projects is desired, but not strictly necessary, in centralized planning settings.

Planning international transmission interconnections involves dealing with many of the difficulties mentioned above, but also requires consideration of additional features. Scale, for instance, is important because assessing the economic benefits of a proposed project between two countries requires concurrent simulation of operations in both systems in order to capture correlations of demand, wind, hydro, and solar profiles (if available). Scale becomes more relevant when evaluating the economic benefits that result from a set of multinational projects in an interconnected system with many independent countries or regions (Perez et al., 2016). However, the computational complexity that involves finding the so-called optimal plan in a large interconnected system (e.g., the one that minimizes expected system costs for the entire region, assuming full coordination among countries) is only a first step in a study of transmission interconnections. The next step involves finding a mechanism for allocating the economic benefits and costs that result from the proposed projects in a fair and efficient manner, such that all hosting countries support their development. Moreover, under certain circumstances, host countries might prefer to build a broader consensus and even consider the effects of new projects on third-party countries. As we mentioned in the previous section, third-party countries can experience positive or negative economic effects as a result of new grid investments elsewhere in the system (Bushnell and Stoft, 1996, 1997).

One mechanism that is often used to support transmission interconnections is the Equal Share Principle (ESP) (Jansen et al., 2015). Under this paradigm, each country hosting a new (bilateral) transmission project is responsible for financing 50% of the capital costs of the transmission project and gets a 50% share the congestion rents that result from the power exchanges between countries at local prices. There are also variants of this mechanism based on the principle that beneficiaries pay (Hogan, 2018). This paradigm is applied in the U.S., where FERC has a rule which establishes that *"(t)he cost of transmission facilities must be allocated to those within the transmission planning region that benefit from those facilities in a manner that is at least roughly commensurate with estimated benefits"* (FERC, 2012).

In 2013, the Agency for the Cooperation of Energy Regulators (ACER) proposed the use of the Positive Net Benefit Differential (PNBD) principle as a mechanism to support transmission interconnections in the EU (ACER, 2013). The PNBD allocates transmission costs in proportion to estimated (positive) benefits as a result of new transmission projects. Konstantelos et al. (2017b), for example, compares two different versions of the mechanism. In one version, third-party countries that are worse off as a consequence of the new infrastructure are compensated through side payments from hosting countries that leaves them with zero net benefits compared to a reference case (e.g., no interconnections). These compensations are also prorated in proportion to estimated benefits. In the other version, third-party countries are not considered for compensation payments, which reduces the complexity of the mechanism. However, this variant might result in free-riding issues that could lead to political conflicts among countries (Jansen et al., 2015). While the PNBD can indeed help in building broad consensus to implement transmission interconnections because, by design, it results in nonnegative net benefits for all individual countries in a region, there is no economic principle that underlines the final allocation of benefits and costs under this mechanism.

We can think of three weaknesses of the methods mentioned above. First, they neglect the incremental economic value that results from a country's support for one or a set of transmission projects (e.g., changes in net benefits for all countries if one nation decides not to support a project). For instance, countries with abundant flexible generation, such as hydro in Norway, may be responsible for a large fraction of the cost savings that result from an integrated NSOG network. Based on this information, they would probably expect to receive a large fraction of economic benefits in return for providing such flexible resources. Second, these methods also disregard how the deployment sequence of transmission projects can affect estimates of the economic value of the proposed portfolio of grid investments (e.g., incremental value of a project for the system if it is considered first or last in a sequence of installations) (Banez-Chicharro et al., 2017). Finally, they ignore incentives for countries to form smaller subcoalitions and achieve higher payoffs than under a grand cooperative agreement. Any of these features could weaken incentives for countries to join the grand coalition and lead to failure to implement a socially-optimal set of international transmission interconnections (Nylund, 2009).

An alternative allocation mechanism is the Shapley Value from cooperative game theory (Shapley, 1953). By construction, the SV takes into account the average incremental contribution of each country towards the grand coalition, considering all possible development sequences. The result is a fair allocation of net benefits, ignoring strategic incentives for parties to deviate from the grand coalition. However, under certain conditions the resulting allocation can also be stable—meaning that involved parties lack incentives to deviate from the grand coalition. Different versions of the SV have been proposed as frameworks for achieving fair allocations of net benefits among consumers and producers in different locations in a transmission network (Contreras and Wu, 1999, 2000; Zolezzi and Rudnick, 2002; Erli et al., 2005). In a report by the North Seas Countries' Offshore Grid Initiative (NSCOGI, 2014) the authors consider the SV as one possible mechanism to allocate transmission costs among cooperating countries in the NSOG, but that study ignores the possibility of using side payments to achieve a fair distribution of net benefits. To our best knowledge, ours is the first study that proposes the use of the SV as a mechanism to distribute both benefits and costs in the context of international transmission interconnections, such as the NSOG.

3. WHY DECENTRALIZED APPROACHES FOR TRANSMISSION PLANNING MIGHT FAIL TO ATTAIN A SOCIAL OPTIMUM

While international transmission interconnections do require some form of agreement between host countries with direct veto power, centrally-coordinated benefit (or cost) allocation mechanisms (e.g., equal share, PNBD, SV) are not the only option to support the development of new grid projects in an interconnected system. One decentralized, or free-market, alternative is to let countries freely negotiate the final allocation of benefits and costs from a socially-optimal plan of transmission interconnections identified by some international organization (e.g., ENTSO-E or ACER). This could be achieved through an iterative process of multilateral bargaining (Krishna and Serrano, 1996), where each country negotiates the minimum share of net benefits that it would be willing to receive based on its bargaining power. For example, a host country with the power to veto a transmission project that results in large economic net benefits for all neighbors in the region has strong bargaining power. It is likely that this country will only agree to host the new transmission line if it gets a large share of those net benefits. Furthermore, a third-party country that will experience positive net benefits as a result of a new project might voluntarily join the negotiations and offer to bear a share of the development costs. Host countries might also consider it beneficial to provide some form of economic compensation to third parties that will be worse off if the cost of political tensions outweigh the costs of providing such compensations.

In theory, if there are well-defined property rights and no transaction costs, a decentralized bargaining mechanism could achieve an efficient outcome (Anderlini and Felli, 2006), in line with the *Coase Theorem*. However, there are some features of the bargaining mechanism that could result in a failure to implement a socially-optimal set of transmission interconnections. First, the Nash bargaining solution does not always lead to a socially-optimal outcome (i.e., the one that is optimal for the grand coalition) if there are more than two agents involved in the negotiation. This is because the optimal solution of the Nash bargaining problem ignores the possibility of cooperation among subsets of players (Narahari, 2014). Consequently, if all subcoalitions can negotiate effectively, agents will have incentives to deviate from the bargaining problem that involves all parties if some subcoalition offers more net benefits than what they would get under the grand coalition (Myerson, 1997). Second, bargaining can be costly due to transaction costs or discounting factors if parties are impatient. In such settings, trade can yield an inefficient allocation of net benefits and, in some cases, it might not even occur (Perry, 1986; Cramton, 1991; Anderlini and Felli, 2006). Third, in a decentralized planning setting, countries could act strategically by over or underinvesting in local infrastructure projects that would shift rents to their constituents (Huppmann and Egerer, 2015), which would then deviate investments from the socially-optimal ones. Finally, Joskow and Tirole (2005) provide strong arguments against the thesis that multilateral bargaining will effectively lead to an agreement among all winning and losing parties as a result of large and lumpy transmission projects (i.e., the Coase Theorem).

Merchant transmission investments can also be used as a decentralized solution to international transmission interconnections. These rely on competition and market-based pricing to incentivize new transmission capacity. It has been demonstrated that under a certain set of conditions that include nodal pricing, perfect competition, well-defined property rights, and no increasing returns to scale, all profitable transmission investments are efficient investments (Hogan, 1992; Bushnell and Stoft, 1996, 1997). Unfortunately, the converse is not true and not all socially-optimal investments are profitable. Doorman and Frøystad (2013), for instance, show that many transmission interconnection alternatives between Great Britain and Norway do increase social welfare (net of transmission investment costs), however, they are not profitable from a merchant perspective. Egerer et al. (2013) reach the same conclusion, but considering more investment alternatives in the region. Gerbaulet and Weber (2018) repeat the analysis for the region using a more sophisticated approach, where there is a merchant investor that makes decisions anticipating an optimal response of the regulator in building other transmission lines (i.e., as a Stackelberg leader). While in this case merchant investments can capture nearly 70% of the welfare gains that result from transmission interconnections, almost all of those gains are collected by the merchant transmission firm and some countries end up worse off as a result of these developments. However, all of these studies rely on a series of strong assumptions. Joskow and Tirole (2005) show that merchant transmission projects can yield much worse results than expected if, for instance, electricity prices are distorted due to market power of generation firms or if there is gaming between independent merchant transmission investors. For these reasons, few merchant transmission projects have been approved by the EU Commission and seeking approval for new ones has become much more difficult over time (Cuomo and Glachant, 2012).

4. COMPARATIVE STATICS OF TWO- AND THREE-NODE SYSTEMS

In this section we present some counterintuitive effects of transmission investments on welfare at aggregate and regional (i.e., nodal) levels using two stylized networks. We show that although more trading of electricity between regions, as a result of new transmission capacity in congested lines, always result in nonnegative changes of welfare and net welfare[4] in aggregate terms, changes in benefits or costs as a consequence of more trading can be unevenly distributed among regions. In fact, transmission capacity that is optimal from a system-wide perspective (i.e., that maximizes aggregate welfare for all regions) could leave some regions worse off, which can create difficulties for the development of new projects that are not centrally coordinated since the involved parties might not have incentives to support them.

We assume that the demand for electricity at each node is inelastic (i.e., the demand does not respond to changes in price), with a high price ceiling equal to the value of lost load (VOLL).[5] Moreover, we assume linear long-run supply functions and perfect competition. The analysis is static, meaning that we look at one representative market state, with and without additional transmission capacity. Finally, we choose to isolate the impact of congestion rents (CRs) on welfare metrics in both examples because CRs and transmission investment cost cancel each other out at socially-optimal investment levels under ideal conditions (e.g., no increasing returns to scale, no market power, efficient nodal prices, free entry, etc.) (Hogan, 2018; Joskow and Tirole, 2005).

4.1 Asymmetric benefits in a two-node system

Consider first a system composed of nodes (countries) 1 and 2, with demands d_1 and d_2, respectively, such that $d_1 < d_2$, and a transmission line with capacity K. We denote generation levels at each node q_1 and q_2 and assume linear supply functions, $c_1(q_1) = c_0 + a_1q_1$ and $c_2(q_2) = c_0 + a_2q_2$, which represent the long-run marginal cost of generation at each node. Node 2 has a generation mix with a higher marginal cost than generation at Node 1, thus, we assume $a_2 > a_1$. Since $VOLL >> 1$, demand is never curtailed and total demand equate total generation; $d_1 + d_2 = q_1 + q_2$. For simplicity, we only consider transmission capacities K that result in a congested line between nodes 1 and 2. This is true as long as the capacity K induce higher generation costs than what could be achieved by the cheapest generator alone, i.e. the marginal cost of supplying both node 1 and 2 with generator capacity at node 1; $c_1(d_1 + d_2) < c_1(d_1 + K) + c_2(d_2 - K)$, where $0 \leq K \leq d_2$. Consequently, the equilibrium quantities and prices are $q_1 = d_1 + K$ and $p_1 = c_1(d_1 + K)$ for the exporting node, and $q_2 = d_2 - K$ and $p_2 = c_2(d_2 - K)$ for the importing node. Table 1 summarizes dispatch levels, prices, and welfare metrics per node for this system.

Figure 1 shows changes in nodal welfare (W_i), consumer surplus (CS_i), producer surplus (PS_i), and congestion rent (CR) when increasing the capacity of the line from $K = 0$ to $K > 0$, disregarding any transmission cost. The consumer surplus is the area below the VOLL and above the price, p_i, i.e. the surplus that the consumers see in terms of their maximum willingness to pay for electricity. Contrary, the producers see a surplus between their marginal cost of production and the price, p_i. The CR is determined by the price difference and trade/capacity between two, or more, connected nodes. CR is therefore zero when the trade-capacity is zero.

The following assertions are true for this system:

1. *Consumer surplus:* An increase in K benefits consumers at the importing node ($\frac{dCS_2}{dK} = a_2d_2 > 0$) since the price declines ($\frac{dp_2}{dK} = -a_2 < 0$). In contrast, consumers at the exporting node are worse off as a result of an increase in the transmission capacity between nodes 1 and 2 ($\frac{dCS_1}{dK} = -a_1d_1 < 0$) since exports drive local prices up ($\frac{dp_1}{dK} = a_1 > 0$).

[4] In this article we define net welfare as welfare (i.e., the sum of consumer and producer surplus) plus congestion rents.
[5] The value of lost load reflects the economic cost of curtailing one MWh of electricity demand. Here we use it as an estimate of the maximum willingness to pay for an additional unit of energy.

Table 1: Equilibrium results for nodes 1 and 2. Note that transmission investment costs are disregarded from welfare metrics. For net welfare we assume that nodes 1 and 2 receive a fraction of congestion rents equal to α_1 and α_2, respectively, such that $\alpha_1 + \alpha_2 = 1$ (e.g. $\alpha_1 = \alpha_2 = 0.5$).

Metric	Node 1	Node 2	System
Dispatch levels	$q_1 = d_1 + K$	$q_2 = d_2 - K$	$q_1 + q_2 = d_1 + d_2$
Price	$p_1 = c_1 = c_0 + a_1 q_1$	$p_2 = c_2 = c_0 + a_2 q_2$	–
Producer Surplus (PS)	$\frac{1}{2}(p_1 - c_0)q_1$	$\frac{1}{2}(p_2 - c_0)q_2$	$PS_1 + PS_2$
Consumer Surplus (CS)	$(VOLL - p_1)d_1$	$(VOLL - p_2)d_2$	$CS_1 + CS_2$
Congestion Rent (CR)	$\alpha_1(p_2 - p_1)K$	$\alpha_2(p_2 - p_1)K$	$CR_1 + CR_2$
Welfare (W)	$PS_1 + CS_1$	$PS_2 + CS_2$	$PS + CS$
Net Welfare (W+CR)	$PS_1 + CS_1 + \alpha_1 CR_1$	$PS_2 + CS_2 + \alpha_2 CR_2$	$PS + CS + CR$

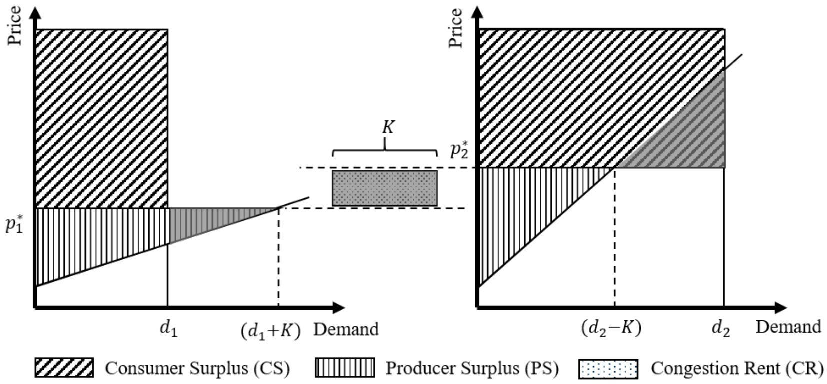

Figure 1: Net welfare effects (dark shaded areas) of new transmission capacity between a low price area (Node 1) and a high price area (Node 2).

2. *Producer surplus:* Producers at Node 1 benefit from an increase in K ($\frac{dPS_1}{dK} = a_1(d_1 + K) > 0$) as the nodal price increase (see 1.). Some production at Node 2 falls out of the market when the price decreases due to cheaper import from Node 1, which reduces producer surplus ($\frac{dPS_2}{dK} = a_2(K - d_2) < 0$).

3. *Congestion rent:* $CR = (p_2 - p_1)K$ is a concave and quadratic function on K. The level K^M maximizes CR and is equal to the optimal investment level for a single merchant investor (disregarding investment costs). The level $K^* = 2K^M$ solves $CR(K) = 0$ and is equal to the socially optimal investment level, which could be achieved under full cooperation between nodes. Thus, $\frac{dCR}{dK} > 0$ for $0 < K < K^M$ and $\frac{dCR}{dK} < 0$ for $K^M < K < K^*$.

4. *Welfare:* If we disregard CR, welfare at Node 1 increases ($\frac{dW_1}{dK} = a_1 K > 0$) when the transmission capacity K increases. Welfare does also increase at Node 2 ($\frac{dW_2}{dK} = a_2 K > 0$) but at a higher rate than in Node 1 ($\frac{dW_2}{dK} > \frac{dW_1}{dK}$) since $a_2 > a_1$. Say CR is split between nodes 1 and 2 in proportions $\alpha_1 \geq 0$ and $\alpha_2 \geq 0$, respectively, such that $\alpha_1 + \alpha_2 = 1$. For $0 < K < K^M$, a marginal increase in transmission capacity always increases net welfare for both nodes, i.e. $\frac{dW_i}{dK} + \alpha_i \frac{dCR}{dK} > 0$ for $i \in \{1, 2\}$.[6] In contrast, for $K^M < K < K^*$ it is possible that a marginal increase in transmission capacity could reduce net welfare in one node for some allocation rule

[6]This is because for $0 < K < K^M$, $\frac{dCR}{dK} > 0$.

(i.e., α_1 and α_2) of CR. Yet, since $\frac{dW_1}{dK} + \frac{dW_2}{dK} + \frac{dCR}{dK} > 0$,[7] it is always possible to split the benefits of adding a marginal amount of transmission capacity to both nodes (e.g., through some form of side payments) such that the marginal change in net welfare is strictly positive at both locations.

When ignoring the allocation of investment costs and CRs in a perfectly competitive market, we see from Figure 1 and the analytical assertions that the aggregated welfare and net welfare always increases when adding capacity to a congested line. However, nodal benefits are unlikely to be evenly distributed since $\frac{dW_2}{dK} > \frac{dW_1}{dK}$, $PS_1 \leq PS_2$, and $CS_1 \geq CS_2$. Hence, some form of compensation could be required since agents at one node could unilaterally block the development of a transmission project. For instance, if we consider investment costs, one could compensate for unevenly distributed benefits by adjusting the allocation of capital cost of new transmission capacity in proportion to the benefits that result from its development (Hogan, 2018). However, under ideal conditions, this cost is equal to CRs (i.e., the line is expanded until the marginal cost of expansion is equal its marginal benefit to the system). Additionally, as we mentioned it in Section 2, such cost-allocation schemes do not take into account the incremental value of each country's support towards a socially-optimal transmission project (e.g., the power to veto the construction of a transmission interconnection). Of course, planning in the real world is much more difficult because, contrary to what we assume in these examples, transmission investments present economies of scale and capacity cannot be expanded in small increments (Joskow and Tirole, 2005; Munoz et al., 2013).

4.2 Asymmetric and negative benefits in a three-node system

We now add a medium price node to the previous example, as shown in Figure 2. The parameter K_{23} denotes the transmission capacity between nodes 2 and 3. Let's assume that the given prices reflect the connected system under operation and that there is a bilateral, voluntary, agreement to build a new transmission line between Node 1 (low price) and Node 2 (high price). Node 3 (medium price), with marginal cost $c_3(q_3) = c_0 + a_3 q_3$ and energy balance $q_3 = d_3 + K_{23}$, is still connected to Node 2 after the new transmission line is built. With more transmission capacity between Node 1 and Node 2 the system is re-dispatched to utilize the cheap generation capacity available at Node 1, meaning that the power flow from Node 3 to Node 2 (K_{23}) decreases to zero as K increases.

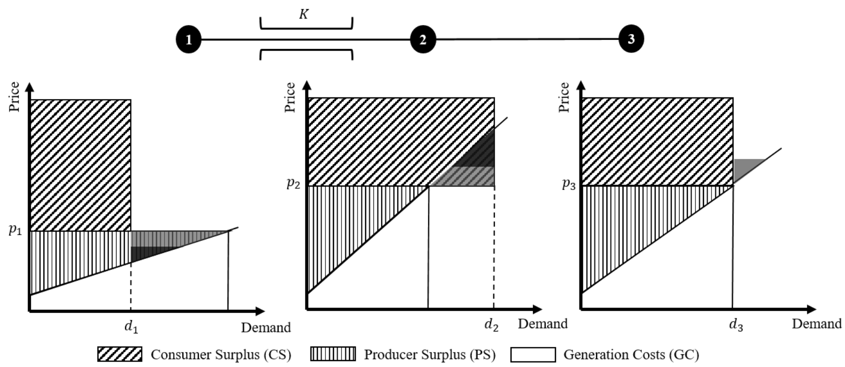

Figure 2: Three-node example where new transmission capacity is added between Node 1 (low price) and Node 2 (high price). Dark shaded areas illustrate the case where it already exists some capacity between Node 1 and 2, while the light shaded areas are the final effects when new capacity is added.

[7]By definition, $a_2 d_2 - a_1 d_1 > 0$, thus $\frac{dW}{dK} + \frac{dCR}{dK} = \frac{K}{2}(a_1 + a_2) + a_2 d_2 - a_1 d_1 > 0$ for $K < K^*$.

The dark shaded areas in Figure 2 show the initial welfare effects of the transmission capacity between Node 1 and 2. When additional transmission capacity (K) is added between Node 1 and Node 2, the system is re-dispatched and welfare increases in these two adjacent nodes (illustrated with the light shaded areas in Figure 2). Simultaneously, as K increases, Node 3 suffers a welfare loss due to less export to Node 2 over K_{23}, since Node 2 imports cheaper electricity from Node 1, i.e. $q_3 = d_3 + K_{23} - K$. Moreover, the CRs accrued between Node 2 and Node 3 decrease due to less trade.

As in the two-node example, the marginal changes in welfare for these three nodes are highly dependent on the slopes of the supply curves at each node. Node 2 has the steepest supply curve and, consequently, experiences the largest change as a result from an increment in the transmission capacity between nodes 1 and 2. Since Node 3's exports are substituted by new trade capacity between nodes 1 and 2, the marginal change in welfare in Node 3 becomes negative, despite the fact that Node 3 has medium-priced generation resources ($a_1 \leq a_3 \leq a_2$). This results in $\frac{dW_2}{dK} \geq \frac{dW_1}{dK} \geq \frac{dW_3}{dK}$, where $\frac{dW_3}{dK} = a_3(K - K_{23}) \leq 0$ as long as the new capacity is lower than, or equal to, the existing capacity between node 2 and 3 ($K \leq K_{23}$).

The three-node system demonstrates that net benefits might not only be unevenly distributed among nodes, or regions, but potentially negative in cases where a new transmission line leads to lower utilization of other, existing lines. This means that the value of some existing transmission rights can potentially decrease to zero after a voluntary, bilateral investment between two nodes elsewhere in the system. This example illustrates why third-party countries should be considered if the approval to build international transmission interconnections requires a broad consensus among all countries in a region, as in the spirit of Regulation (EU) No 347/2013 (EUL, 2013).

5. PROPOSED METHODOLOGY

5.1 Transmission and Generation Planning Model

We use a planning model based on previous work by Trötscher and Korpås (2011), Munoz et al. (2014) and Svendsen and Spro (2016) which has been customized for offshore grid applications (Kristiansen et al., 2017, 2018). To this end, we only provide a high-level overview of its most relevant features supplemented with a detailed description of all variables, parameters, constraints, and its objective function in the Online Appendix. This model captures the problem of a central transmission planner that must select interconnections trying to maximize aggregate welfare for all countries in the region. We assume that all transmission investment decisions are made proactively, anticipating generators' best response to grid developments. In general, finding a solution to this problem involves the implementation of sophisticated algorithms to compute a market equilibrium (Sauma and Oren, 2006). However, since we assume perfect competition in generation investments and operations, inelastic demand, and discrete transmission investments, the above equilibrium problem can be reformulated as a mixed-integer linear optimization program where the objective is to minimize Total System Cost (Samuelson, 1952; Munoz et al., 2014, 2017), where:
Total System Cost = Cost of new transmission interconnections + Cost of new generation capacity + Operational cost of generators + Cost of CO_2 emissions + Cost of curtailed demand

This is subject a series of constraints, some of which include:

- **Supply-demand balance** at each bus in the network in every period. These restrictions take into account imports and exports of power through existing transmission lines and new interconnections. The Lagrange multipliers of these constraints define long-term electricity prices when transmission investments are fixed to their optimal levels.
- **Maximum generation limits**, considering both existing and new generating capacity. We capture the variability of hydro, wind, and solar resources using hourly availability factors from

historical data for each different location in the network. This means that we are able to account for a variety of power flow patterns in the system, while also capturing synergistic effects of the geographical flexibility provided by grid expansion.

- **Thermal limits** on existing transmission lines and on new transmission interconnections.
- **Discrete transmission investment alternatives**, i.e. a transmission line can be built or not built. Additionally, the number of lines per corridor is also determined in order to calculate realistic costs for bulky capacity levels (e.g. related to transformers and power electronics (Härtel et al., 2017b)).

5.2 Computing the Shapley Value

We use the Shapley Value to calculate a fair allocation of net benefits based on each country's contribution to value-creation in transmission interconnections. This mechanism has been used before in different contexts, including problems of maintenance cost allocation at airports (Littlechild and Owen, 1973), as a splitting rule of remaining assets under bankruptcy (O'Neill, 1982), and as a metric to determine the contribution of different energy policies towards a social goal in the context of a combined set of regulations (Murphy and Rosenthal, 2006).

We define a characteristic function, $v(S)$, as the difference in net benefits (i.e., sum of consumer surplus, consumer surplus, and congestion rents) that result from solving the planning problem described in Section 5.1 under the support of coalition S towards the development of new transmission infrastructure and a Base Case, where no transmission projects are developed. We assume that under coalition S, the only transmission interconnections that can be developed are those that are directly connected to host countries that have the power to veto the construction of any lines. For instance, when computing $v(S)$, an interconnection that goes from country A to country B is considered a candidate investment alternative only if $A \in S$ and $B \in S$. If there is no cooperative agreement among host countries and no transmission interconnections can be built, the value function is $v(\emptyset) = 0$. On the other hand, if N is the set that represents the grand coalition (i.e., when all countries reach a cooperative agreement), then $v(N)$ is equal to the total net benefits that would result when considering all transmission interconnections as investment alternatives. Under perfect competition, $v(N)$ is also equal to the welfare gains or net benefits that result from these transmission projects. Following the spirit of Regulation (EU) No 347/2013 (EUL, 2013), we assume that third-party countries will be included in the negotiations. However, for a different application these could be excluded from the computation of the SV by only considering net benefits for host countries in the value function.

$$\phi_i(N, v) = \frac{1}{|N|!} \sum_{S \subseteq N \setminus \{i\}} |S|!(|N| - |S| - 1)![v(S \cup i) - v(S)] \tag{1}$$

In Equation (1) above, $\phi_i(N, v)$ denotes the resulting payoff to each country i under the SV. The expression $[v(S \cup i) - v(S)]$ is the increment in net benefits that results when country i joins the coalition S (i.e., its incremental contribution), which could be formed in $|S|!$ different ways prior to country i joining it. Also, there are $(|N| - |S| - 1)!$ ways the remaining countries could join the same coalition. The product of these expressions summed over all combinations of subsets excluding i ($S \subseteq N \setminus \{i\}$) and divided by $|N|!$ can be interpreted as the average incremental contribution of country i to the grand coalition. The n-tuple $(\phi_1(N, v), \phi_2(N, v), ..., \phi_n(N, v))$ is the final allocation of net benefits for all countries under the SV if $n = |N|$.

The SV is the only allocation that satisfies the properties of efficiency (all benefits are distributed among countries), symmetry (countries with the same average incremental contribution receive the same allocation of benefits), linearity, and zero player (countries that do not have veto power get zero net benefits) (Narahari, 2014). In economics, these properties provide an axiomatic definition of fairness (Myerson, 1977). It has been also demonstrated that, under certain conditions, a process of decentralized sequential bargaining among agents converges to the SV (Gul, 1989).

6. CASE STUDY: NORTH SEA OFFSHORE GRID

We study a portfolio of three transmission interconnections that are planned in the North Sea area, surrounded by six countries in total: Norway (NO), Denmark (DK), Germany (DE), The Netherlands (NL), Belgium (BE), and Great Britain (GB) (see Figure 3). Table 2 summarizes the main characteristics of the three transmission investment alternatives: the North Sea Link (NO-GB), the NordLink (NO-DE), and the Viking (DK-GB) (dashed lines in Figure 3). We assume that, if built, these transmission interconnections will be in operation by 2030 under ENTSO-E's scenario Vision 4 (ENTSO-E, 2016).[8] We consider a planning horizon of 30 years with a discount rate of 5%. An overview of key input data can be found in Table 6 in the Online Appendix.

Table 2: Investment alternatives in transmission interconnections. The cost item includes the net present value of investment, operation and maintenance expenses based on estimates from Härtel et al. (2017b).

Project	From	To	Capacity [MW]	Cost [bn€]
North Sea Link	NO	GB	1400	2.73
NordLink	NO	DE	1400	2.16
Viking	DK	GB	1400	2.50

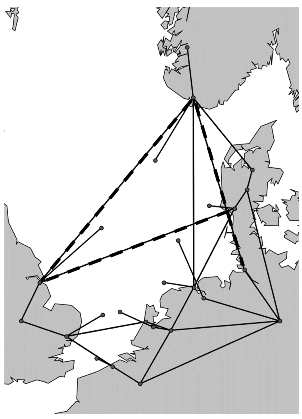

Figure 3: Illustration of the North Sea 2030 case study including all transmission lines that are scheduled to be in operation by year 2030. Candidate branches are shown as dashed lines.

6.1 Computing net benefits for all portfolios of transmission interconnections

We solve the planning problem for the eight possible combinations of investments in transmission interconnections (i.e., 2^3). Table 3 shows the difference in net benefits in equilibrium for each portfolio with respect to the Base Case, where no transmission interconnections are built. Note that all portfolios

[8]ENTSO-E's Vision 4 is a top-down scenario developed at an European level and it is designed to meet the objectives of the European Commission on market integration and on climate-change mitigation. It is considered the most ambitious scenario in terms of investments in renewable generation capacity.

result in positive net benefits with respect to the Base Case, but it is the portfolio that includes all three interconnections (1,1,1) that results in the greatest welfare gains (€25.3bn). Therefore, building the three interconnections is the socially-optimal plan from a central planner's perspective and it is equivalent to what could be achieved under full cooperation among all countries.

Table 3: Aggregate results for the eight possible portfolios of transmission interconnections. Each tuple denotes binary investment decisions (1 if it is built, 0 otherwise) in the following order (North Sea Link, NordLink, Viking). All values for portfolios other than the Base Case are measured relative to the Base Case (0,0,0). Net benefits are in net present value for the 30-year planning horizon and normalized to zero for the Base Case.

	Net benefits [bn€]	Average price [€/MWh]	Cost of CO_2 emissions [bn€]	Transmission investment [bn€]	Generation investment [bn€]	Renewables % of generation
Base case	0	68.92	183.15	0	1.34	58.55
(0, 0, 1)	6.1	-0.12	-1.50	2.50	-0.02	0.17
(0, 1, 0)	8.8	-0.16	-8.90	2.16	-0.00	0.27
(0, 1, 1)	15.0	-0.31	-10.40	4.66	-0.02	0.46
(1, 0, 0)	11.2	-0.25	-3.11	2.73	-0.02	0.24
(1, 0, 1)	16.5	-0.40	-4.91	5.23	-0.02	0.52
(1, 1, 0)	19.1	-0.42	-11.99	4.89	-0.02	0.52
(1, 1, 1)	25.3	-0.55	-13.84	7.40	-0.02	0.81

We compute the average price of electricity for each transmission portfolio as a load-weighted average for all operating hours and across all regions. The social cost of carbon emissions is equal to the value of the carbon tax (76 €/ton, in line with ENTSO-E (2016)) times total emissions in the system (ton CO_2). Investment costs are separated into transmission investments and generation investments. We also include the resulting share of generation from renewable energy technologies as a fraction of total energy production. Note that the share of renewables is relatively high for all transmission configurations because we assume that the amount of installed generating capacity is equal to what it is outlined in ENTSO-E Vision 4, a very ambitious scenario for 2030 in terms of renewable penetration. While here we only focus on net benetifs from transmission interconnections, it is worth mentioning that there are also other potential benefits from these projects that could be relevant for countries in the region. Some of these include reductions in average electricity prices and carbon emissions, as well as higher shares of generation from renewable energy technologies with respect to a Base Case without interconnections.

6.2 A fair allocation of net benefits under the Shapley Value

We compute the Shapley Value using the methodology described in Section 5.2 and the results described in Table 3. Recall that the SV supports the socially-optimal portfolio of transmission interconnections under the assumption that all countries will reach a cooperative agreement. The SV also provides a fair allocation of net benefits for all countries in the region considering their average incremental contribution to the grand coalition. Figure 4 shows the final allocation of net benefits for all countries in the NSOG with respect to the Base Case (i.e., when no transmission interconnections are built).

First of all, note that the SV suggests that Norway should receive the largest fraction of net benefits (nearly €10bn) among all six countries as a result of the three new transmission interconnections. This is because Norway has the power to veto two of the proposed interconnections: the North Sea Link (NO-GB) and the NordLink (NO-DE). Similarly, Great Britain should receive the second largest fraction of net benefits (nearly €8bn) because it could unilaterally veto the development of the North Sea Link (NO-GB) and the Viking (DK-GB). The economic intuition behind the difference in the allocation of net benefits for Norway and Great Britain can be explained by the difference in net benefits that result from the construction of the three candidate projects. While the SV considers all the possible sequences of development of these interconnections, one can gain some insights by,

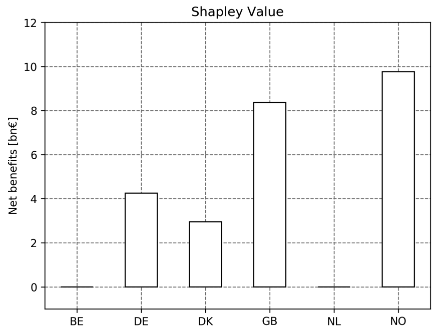

Figure 4: A fair allocation of net benefits per country under the Shapley Value. Values are measured with respect to the Base Case (0,0,0).

for instance, comparing the incremental net benefit of developing just one of the three projects with respect to the Base Case (0,0,0). The nef benefits that result from developing either the North Sea Link (1,0,0), the NordLink (0,1,0), or the Viking (0,0,1) with respect to the Base Case are €11.1bn, €8.8bn, and €6.1bn, respectively. Based on these numbers, Norway should be allocated a larger fraction of net benefits than Great Britain because it has the power to veto the construction of the two most valuable interconnections, the North Sea Link and the NordLink, whereas Great Britain could only block a set of two less valuable projects, the NordLink and the Viking.

Interestingly, one would reach the same conclusion when considering the incremental value of adding any of the three projects when the other two interconnections are already in place. For instance, the value of adding the North Sea Link is equal to the incremental net benefit of going from portfolio (0,1,1) to (1,1,1). The net benefits that result from adding either the North Sea Link, the NordLink, or the Viking with respect to scenario where the other two projects have been already developed are equal to €10.3bn, €8.8bn, and €6.2bn. Again, Norway has the power to veto projects that are more valuable than the projects that could be blocked by Great Britain and, consequently, Norway should receive a larger fraction of the net benefits that result from the development of the three interconnections. We want to highlight that the incremental value that results from a country joining a coalition also reflects the value of the resources that become available for the rest of countries in a system. For instance, the system as a whole will benefit from new transmission interconnections to Norway's flexible hydropower resources that cause no direct carbon emissions.

Note that both Denmark and Germany should also receive positive net benefits based on their average incremental contribution to the grand coalition. However, the share of net benefits allocated to these countries is nearly half of what should be allocated to Norway and Great Britain. What explains this difference is that Denmark could only veto the Viking and Germany could only block the construction of the NordLink, therefore, their incremental contribution to the cooperative agreement is lower than the one by Norway and Great Britain. The difference in allocated net benefits between Denmark and Germany is rooted in the economic value of the project that they could unilaterally block. The Viking has a lower incremental value for the system than the NordLink, which means that Germany should be allocated a larger fraction of net benefits than DK.

Third-party countries, Belgium and the Netherlands receive zero net benefits as a result of the new transmission interconnections because they have no power to veto the construction of any of the three lines (i.e., their incremental value to the grand coalition is zero). This means that, under the SV, third-party countries are indifferent to the development of the three proposed transmission interconnections.

6.3 Comparing final allocations of net benefits under the Shapley Value relative to two conventional mechanisms: the Equal Share Principle and the Positive Net Benefit Differential

Here we consider two conventional allocation mechanisms that have been used in existing transmission interconnections. The first one divides the capital costs of transmission interconnections and congestion rents between host countries in equal shares (i.e., 50 % to each country). Following the terminology in Jansen et al. (2015), we refer to this allocation mechanism as the Equal Share Principle (ESP). The second mechanism is the Positive Net Benefit Differential (PNBD), which allocates the capital cost of transmission interconnections in proportion to estimated benefits (including congestion rents).[9]

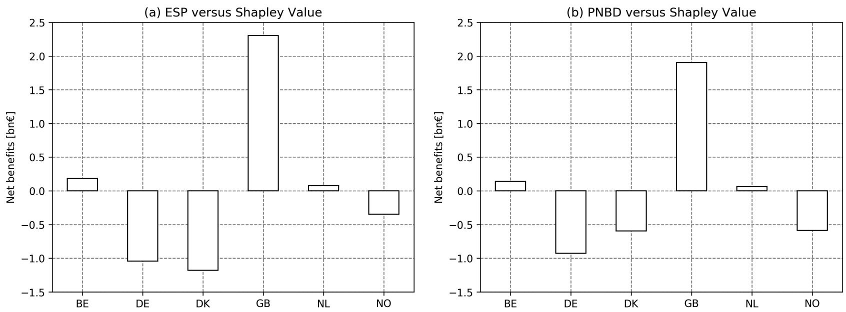

Figure 5: Relative differences of net benefits per country when comparing the (a) Equal Share Priciple (ESP) and the (b) Positive Net Benefit Differential (PNBD) with respect to the Shapley Value. Positive values indicate that countries are overcompensated relative the SV allocation.

Figure 5 (a) shows the relative difference between the final allocation of net benefits under the ESP and the SV and Figure 5 (b) shows the difference between the final allocation of net benefits between the PNBD and the SV. Note that under the ESP, Great Britain would receive €2.3bn more of net benefits than under the SV. Since Norway will receive nearly €0.25bn less of net benefits than under the SV, under the ESP, Great Britain will end up receiving almost €1bn more net benefits than Norway, even though Norway has the power to veto the two most valuable proposed interconnections. This could complicate negotiations because Norway could refuse to accept the construction the North Sea Link and the NordLink unless it receives a larger share of net benefits than Great Britain. Moreover, the negotiations with both Germany and Denmark could also become difficult because under the ESP their final shares of net benefits are nearly 25% and 33% lower than their average incremental contribution to the grand coalition, respectively. Again, this is because the ESP ignores the power of host countries to veto the construction of new transmission interconnections. Belgium and the Netherlands will free ride on the rest of the countries in the NSOG because they will bear no costs, even though the new interconnections will provide positive net benefits to these two third-party countries.

Splitting transmission costs in proportion to estimated net benefits, as in the PNBD, will result in an allocation that is slightly closer the SV (Figure 5 (b)). Great Britain, for instance, will bear a larger share of transmission costs and, consequently, receive a lower share of net benefits than under the ESP (nearly €0.35bn less). Likewise, both Germany and Denmark will bear a lower share of transmission costs and end up with a larger share of net benefits than under the ESP. However, the change will be rather small with respect to the ESP. Net benefits for Great Britain will remain larger

[9] Here we consider the first variant of the PNBD described in Jansen et al. (2015) which is based on the beneficiary pays principle (Hogan, 2018), meaning that transmission costs are distributed among all countries in the interconnected system. The second variant limits the distribution of costs to host countries only (Konstantelos et al., 2017b).

than for Norway, and both Germany and Denmark will continue to receive a disproportionately small fraction of net benefits compared to their average incremental contribution to the grand coalition. Third-party countries will still free ride on host countries, as under the ESP, because their allocated share of transmission costs is too small compared to what it would be fair under the SV. Furthermore, Norway will be worse off under the PNBD because it will be responsible for bearing a larger share of transmission costs than under the ESP. While this is in line with cost-allocation rules used elsewhere, ignoring the power of this country to veto the two most valuable proposed projects could lead to failure to reach a cooperative agreement among all countries in the region. These two examples illustrate why more sophisticated mechanisms for allocating benefits and costs, such as the SV, could provide stronger incentives for cooperation than conventional mechanisms such as the ESP and the PNBD.[10]

6.4 Achieving the Shapley Value through a set of Power Purchase Agreements

In the previous section we showed that there are important differences between the final allocations of net benefits under the SV and the two conventional mechanisms. One alternative to achieve the SV is to initially support the development of new transmission interconnections using one of the conventional allocation approaches and then implement a mechanism of side payments that would result in the desired allocation of net benefits over the planning horizon. Figure 6 shows the side payments required to achieve the SV in our case study, assuming that interconnections will be initially supported using the ESP. However, it is not clear if such mechanism would be implementable in practice. The main limitation of this approach is that it would involve large transfers of net benefits among countries—ranging from €80m to €2300m in our case study—*before* these benefits are even realized.

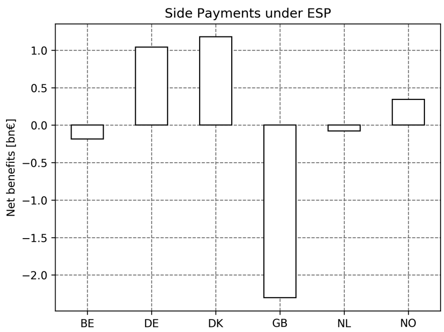

Figure 6: Side payments required to achieve the allocation of net benefits under the Shapley Value if interconnections are initially supported through the ESP. Positive values represent compensations while negative values are payments to the cooperative interconnection fund. All side payments add up to zero.

One alternative to achieve the SV as countries trade power over time would be the implementation of a set of Power Purchase Agreements (PPAs) and a *cooperative interconnection fund*. Under this mechanism, the cost of new transmission interconnections and congestion rents could be initially divided through a conventional mechanism, such as the ESP or the PNBD. A coordinating organization (e.g., ENTSO-E or ACER) could then estimate the required side payments to achieve a

[10] In fact, in Sections 8.4 and 8.5 in the Appendix we verify that neither the ESP nor the PNBD are in the core of the game because third-party countries receive positive net benefits. This means that both allocation rules are unstable. We also verify that, if the planning problem is considered a non-cooperative game, then the efficient solution is a Nash equilibrium (see Table 8 in the Online Appendix). This is because host countries do not have incentives to deviate from the Nash equilibrium and veto transmission projects. However, this ignores bargaining considerations, such as the power of Norway to block the construction of the two most valuable transmission lines if it receives a smaller fraction of net benefits than Great Britain.

fair allocation of net benefits under the SV. This set of side payments could be used as a basis for defining a set of PPAs, as contracts for differences, between the interconnection fund and each country in the region.

Let's consider the following contractual agreement. Say PPA_A is the (fixed) contract price for country A, L_A is the set of transmission interconnections to neighboring countries of A (both new and existing), $P^{spot}_{l,t}$ is the hourly price at the node where line l is connected to country A (border node), $f^{exp}_{l,t}$ and $f^{imp}_{l,t}$ are the hourly power flows that, respectively, go out and into country A through line l (both are nonnegative), and $loss_l$ is a loss factor. If country A sells its power (i.e., if $f^{exp}_{l,t} > 0$ and $f^{imp}_{l,t} = 0$) at a fixed price equal to PPA_A but collects $P^{spot}_{l,t}$ for every MWh of power exported through line l, then this country must receive a side payment from the interconnection fund equal to $(PPA_A - P^{spot}_{l,t}) \cdot f^{exp}_{l,t}$ if $PPA_A > P^{spot}_{l,t}$. On the other hand, if $PPA_A < P^{spot}_{l,t}$, then country A must pay a compensation to the interconnection fund equal to $(P^{spot}_{l,t} - PPA_A) \cdot f^{exp}_{l,t}$. The opposite is true if country A imports power at a certain hour (i.e., if $f^{imp}_{l,t} > 0$ and $f^{exp}_{l,t} = 0$). Summing over all transmission interconnections connected to country A, L_A, and over all representative hours in the planning period T[11] (e.g., 8760 hours in a representative year), we can compute the side payment to country A, denoted SP_A, as follows:

$$SP_A = a \cdot \sum_{l \in L_A} \sum_{t \in T} (PPA_A - P^{spot}_{l,t}) \cdot (f^{exp}_{l,t} - f^{imp}_{l,t} \cdot (1 - loss_l)) \qquad (2)$$

If $SP_A > 0$, country A will receive a side payment , otherwise, if $SP_A < 0$, A will pay an economic compensation to the interconnection fund. Note that given an estimate of SP_A from Figure 6, it is possible to find the value of PPA_A such that, over time, country A will ultimately achieve a desired allocation of net benefits. This could be applied to all countries in the region to define the set of PPAs that achieve the desired final allocation of net benefits under the SV. Note that if C denotes the set of countries in the region, then:

$$\sum_{c \in C} SP_c = 0 \qquad (3)$$

This is true because, by construction, side payments are only welfare transfers among countries to achieve the SV (see Figure 6). In the mechanism design literature this property is known as *budget balancedness* (Narahari, 2014).

Table 4: Summary of PPAs per country to achieve the SV. Average prices are weighted by demand. The PPA profit per country is equal to the net compensation received from the cooperative fund every year required to achieve the side payments in Figure 6.

	Net export TWh/yr	PPA €/MWh	Average price €/MWh	PPA profit m€/yr
NO	29.0	20.6	19.9	22.5
DK	8.4	72.4	63.3	76.7
DE	6.1	90.3	79.3	67.8
NL	-25.5	85.4	85.2	-5.0
BE	-22.0	89.3	88.8	-12.0
GB	3.9	35.4	73.8	-149.9

Table 4 above shows values of PPAs to achieve the SV based on the side payments from Figure 6, assuming that interconnections will be initially funded through the ESP. We include the average load-weighted local price of electricity for each country as a reference to give the reader an idea if the PPA determines that power will be exported (or imported) at a price that is, on average,

[11] The parameter a denotes an annuity factor used to compute the discounted sum of annual side payments over the 30-year planning horizon.

higher or lower than the local price of electricity.[12] Norway, for instance, is a net exporter and would need a PPA with a fixed price of 20.6€/MWh—0.7€/MWh higher than the local average price—to receive the desired side payment of €22.5m per year. The Netherlands on the other hand, is a net importer of power and would need to buy power through the existing transmission interconnections at a fixed price of 85.4€/MWh—0.2€/MWh higher than the local average price—to achieve the desired payment of €5m per year to the cooperative interconnection fund.

The main advantage of using PPAs to achieve the SV is that net benefits will be redistributed as countries trade power over time, not prior to their realization. Of course, the set of PPAs proposed here is only one possible alternative to achieve the SV, more elaborate contractual agreements could be used to attain the same objective. For instance, if a country has zero net exports (e.g., annual inflows = annual outflows) it might be more convenient to use a PPA with different base prices for imports and exports for that specific country.

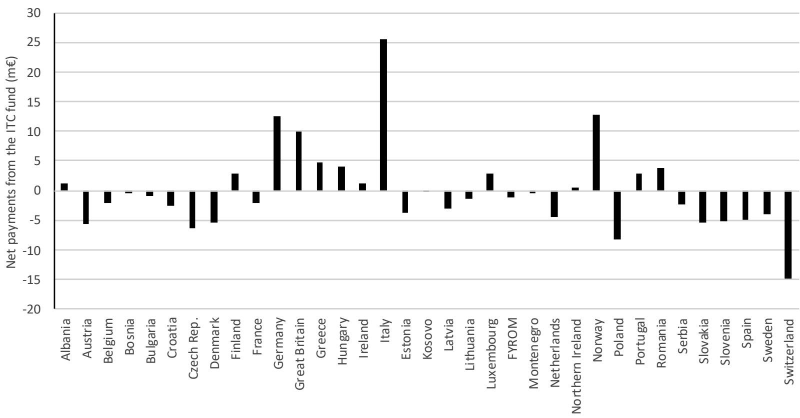

Figure 7: Annual net compensations from the ITC fund per country in 2016. Positive values indicate compensations from the fund to individual countries and negative values are contributions to the fund. Data retrieved from ACER (2017).

Finally, we want to highlight that the proposed mechanism to redistribute net benefits and costs among countries in the NSOG is akin to the existing mechanism for inter-TSO compensations in the EU. The inter-TSO compensation (ITC) mechanism is designed to compensate countries for the cost of making infrastructure available and for the cost of transmission losses for hosting cross-border flows (Hirschhausenm et al., 2012). Figure 7 shows net payments to each country in the EU from the ITC fund in 2016 (ACER, 2017). The ITC fund in 2016 was approximately €258m and, for the same year, net payments from the fund to individual countries were equal to €170m (i.e., sum of all positive values in Figure 7). The total amount of annual compensation payments to the interconnection fund needed to achieve the SV in our case is equal to €166.9m (i.e., sum of all positive PPA profits per year in Table 4). With the exception of the required payment from Great Britain to the fund (€149.9m per year), the required annual net payments to the interconnection fund per country displayed in Table 4 and the current annual net compensations to the ITC fund in Figure 7 are within the same order of magnitude.

[12]Note that the difference between the fixed price of the PPAs and the average load-weighted local prices times net export flows is not equal to the desired side payment. This is because the actual side payments are computed using hourly spot prices that are not weighted by demand. In Table 4 we only provide average load-weighted electricity prices for illustrative purposes.

6.5 Stability of the Shapley Value

The main goal of our article is to describe how the Shapley Value could be used to determine a fair allocation of net benefits among countries that reach a cooperative agreement to develop a set of transmission interconnections. While the SV is the only allocation that is based on the average incremental contribution to the system and that satisfies a set of desirable properties, there is no guarantee that the solution will be stable (Maskin, 2003). This is because some countries could be better off by forming subcoalitions and potentially block the construction of new transmission interconnections.

In cooperative games, an allocation is said to be in *the core* of the game if agents have no incentives to deviate from the grand coalition and form subcoalitions. It has been demonstrated that if a cooperative game is convex, then the SV is in the core (Narahari, 2014). A game is convex if the incentives to join a coalition are weakly increasing on the size of the coalition. Equation 4 shows the property of convexity of a cooperative game, where the incremental value for country i to join coalition T is higher than or equal to the incremental value of joining coalition S, where coalition S is formed by a subgroup of the countries that form coalition T (i.e., $S \subseteq T$).

$$v(S \cup \{i\}) - v(S) \leq v(T \cup \{i\}) - v(T) \qquad \forall S \subseteq T \subseteq N \backslash \{i\}, \forall i \in N \tag{4}$$

While checking for convexity in a generic cooperative game might seem difficult, in our case it is actually very simple. It is mostly a matter of verifying that the incremental value of adding a new transmission interconnection when other lines are already in place is greater or equal than the value of adding the line when at least one of the other lines was not developed. For instance, the incremental value of adding NO to the coalition $S = \{GB\}$ is $v(GB, NO) - v(GB) =$€11.2bn, equal to the value of going from portfolio (0,0,0) (Base Case) to (1,0,0) in Table 3. The incremental value of adding NO to a larger coalition than S, say $T = \{GB, DE\}$, is $v(GB, DE, NO) - v(GB, DE) =$€19.1bn, which is equal to the value of going from portfolio (0,0,0) to (1,1,0). Consequently, the value of adding NO to a coalition T is higher than the value of adding NO to $S \subseteq T$. Since this is also true for the rest of the countries in the NSOG and all possible subsets of the grand coalition, the cooperative game is convex and the final allocation of net benefits computed using the SV is in the core. Consequently, the proposed allocation is not only fair, but also stable because countries have no incentive to deviate from the grand coalition. Although we do not provide a general proof that cooperative games of international transmission interconnections are always convex, verifying whether this property holds, or not, in real-world applications should be relatively simple since these usually have a very limited number of transmission investment alternatives.

Another alternative to evaluate if an allocation rule is in the core of the game is to explicitly write the set of linear inequalities that define the core. These include individual, coalitional, and collective rationality constraints. We include these constraints in Section 8.4 of the Appendix.

7. CONCLUSIONS

In this paper, we present a mechanism for allocating the benefits and costs that result from the development of international transmission interconnections under a cooperative agreement. We focus on this subject inspired by the goal of the EU Commission to integrate markets in order to increase the economic efficiency and security of supply of the electric power system. The integration of markets can also result in reductions of greenhouse gas emissions. Unlike federal rules for interregional transmission planning enforced by FERC in the U.S. (FERC, 2012), the EU Commission has no legal power to impose the development of new transmission interconnections that are deemed efficient between countries in the EU. This means that these projects will only be developed if all involved countries reach an agreement on how to divide the resulting benefits and costs in a fair manner.

Our proposed mechanism is based on the Shapley Value from cooperative game theory and a detailed planning model that takes into account generators' response to transmission investments. The main advantage of the Shapley Value is that it provides a unique allocation of net benefits based on each country's average incremental contribution to the grand coalition. Furthermore, the Shapley Value is the only allocation that fulfills a series of desirable properties that, in the economic literature, are referred to as the axiomatic definition of fairness (Myerson, 1977). This is an improvement over conventional allocation methods because the proposed mechanism explicitly considers the power of each country in the region to veto the construction of new transmission interconnections. Consequently, countries that have the power to block the development of highly valuable transmission projects are allocated a larger fraction of net benefits than countries that can only block projects of low incremental value to the system. In our case study, both Norway and Great Britain are allocated a larger fraction of net benefits than the rest of countries in the NSOG because they can each block two of the three proposed interconnections. In contrast, under the Shapley Value, Belgium and the Netherlands receive zero net benefits from new transmission interconnections because they have no power to veto any of the three proposed projects.

We verify that under two conventional allocation methods, the Equal Share Principle and the Positive Net Benefit Differential, some countries receive a fraction of net benefits that is much larger than their average incremental contribution to the system. The best example is Great Britain, which is allocated nearly €2bn of net benefits in excess of its actual incremental contribution under both conventional allocation mechanisms. In fact, under these allocation rules, Great Britain ends up with a larger share of net benefits than Norway, even though the latter can veto the two most valuable transmission interconnections. The opposite is true for Denmark and Germany, which are undercompensated by nearly €1bn each. Also, under both conventional methods, Belgium and the Netherlands (third-party countries) end up free riding on the rest of the system because they are not required to bear any costs of new infrastructure. We believe that these discrepancies between the actual incremental contribution of each country to the cooperative agreement and the final allocation of benefits and costs under conventional mechanisms could make negotiations difficult or create political tension among countries in the region. The mechanism we propose in this article can help organizations that foster collaboration among countries, such as ENTSO-E, to find a fair manner to split the benefits and costs that result from international transmission interconnections.

We also show that the final allocation of net benefits under the Shapley Value can be used as a basis for defining a set of Power Purchase Agreements, such that countries achieve the desired final allocation of net benefits as they trade power over time. This is similar to the current mechanism for compensations among TSOs in the EU (i.e., the ITC fund), which was implemented to compensate countries for the cost of making their transmission infrastructure available to host cross-border flows and the cost of the resulting transmission losses.

While there is no guarantee that the Shapley Value value will always result in a stable allocation of net benefits (i.e., the Shapley Value is not always in the core of a cooperative game), there is a general result that proves that the Shapley Value is stable if the game is convex. We show that this property can be easily verified in real-world interconnection planning problems because investment alternatives are often limited. In our case study, the final allocation of net benefits under the Shapley Value is convex and, consequently, countries do not have incentives to leave the grand coalition or to veto the construction of any of the three transmission interconnections. However, for some cooperative games, the Shapley Value might not be in the core (e.g., if the game is nonconvex) or the core might be an empty set. It is worth highlighting that an empty core does not imply that the grand coalition will fail to form. Maskin (2003), for instance, shows an example of a cooperative game with an empty core where the grand coalition still forms and agents achieve the Shapley Value through an iterative bargaining process with binding contracts. The author also provides a generalization of the Shapley Value to cooperative games when coalitions exert externalities on other coalitions (e.g., pollution games). The approach proposed by Maskin (2003) is a good alternative to the mechanism we describe in this paper if, for some application, countries prefer to block some of the proposed transmission interconnections. Another alternative to the Shapley Value if a game is nonconvex is the Nucleoulus (Schmeidler, 1969). This approach also provides a unique allocation of net benefits based on bargaining considerations, aiming at minimizing the incentives of the most dissatisfied agent in the game to withdraw from the grand coalition (Narahari, 2014). These alternatives should be explored in future studies.

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8. APPENDIX

Here we present a detailed description of the planning model, a summary of the input data used in our case study of the NSOG, and supplementing results that support our discussions.

8.1 Detailed description of the planning model

Table 5: Notation for the generation and transmission planning model (PowerGIM).

Sets & Mappings	
$n \in N$	: nodes
$i \in G$	: generators
$b \in B$	: branches
$l \in L$	: loads, demand, consumers
$t \in T$	: time steps, hour
$i \in G_n, l \in L_n$	: generators/load at node n
$n \in B_n^{in}, B_n^{out}$	: branch in/out at node n
$n(i), n(l)$	: node mapping to generator i/load unit l
Parameters	
a	: annuity factor
ω_t	: weighting factor for hour t (number of hours in a sample/cluster) [h]
$VOLL$	: value of lost load (cost of load shedding) [€/MWh]
MC_i	: marginal cost of generation, generator i [€/MWh]
$CO2_i$	: CO_2 emission costs, generator i [€/MWh]
D_{lt}	: demand at load l, hour t [MW]
B, B^d, B^{dp}	: branch mobilization, fixed- and variable cost [€,€/km,€/kmMW]
CS_b, CS_b^p	: onshore/offshore switchgear (fixed and variable cost), branch b [€,€/MW]
CX_i	: capital cost for generator capacity, generator i [€/MW]
CZ_n	: onshore/offshore node costs (e.g. platform costs), node n [€]
P_i^e	: existing generation capacity, generator i [MW]
γ_{it}	: factor for available generator capacity, generator i, hour t
P_b^e	: existing branch capacity, branch b [MW]
$P_b^{n,max}$	: maximum new branch capacity, branch b [MW]
D_b	: distance/length, branch b [km]
l_b	: transmission losses (fixed + variable w.r.t. distance), branch b
E_i	: yearly disposable energy (e.g. energy storage), generator i [MWh]
M	: a sufficiently large number
Primal variables	
y_b^{num}	: number of new transmission lines/cables, branch b
y_b^{cap}	: new transmission capacity, branch b [MW]
z_n	: new platform/station, node n
x_i	: new generation capacity, generator i [MW]
g_{it}	: power generation dispatch, generator i, hour t [MW]
f_{bt}	: power flow, branch b, hour t [MW]
s_{nt}	: load shedding, node n, hour t [MW]

We minimize the net present value (NPV) of total system costs and find the socially optimal solution that would be attained under full cooperation among all involved countries. Total costs (1a) include investment costs (1b) and operational costs (1c). Operational costs are calculated for one representative year, multiplied with an annuity factor a in order to convert annual costs to NPV.

Transmission infrastructure investments are represented with both fixed (1d) and variable costs (1e). We determine fixed costs based on mobilization costs B and cable distance $B^d D_j$, in addition to voltage transformers and/or power electronics needed at each end of the cable (CL is the cost for land-based stations and CS is the cost for offshore-based stations). Fixed costs are multiplied by an integer variable that reflects the number of cables, y_b^{num}. Moreover, in the expression that describes the variable costs (1e) there is a power-distance dependent cost parameter $B^{dp} D_j$ and a power dependent cost parameter for the end-points of the branch (CL^p is the cost for land-based stations and CS^p is the cost for offshore-based stations), which is multiplied by new branch capacity, y_b^{cap}. In cases where a node facility does not exist, e.g. an offshore node/platform, a binary variable, z_n, is used to reflect installation costs C_n^{bus} for such a node facility which is forced to be implemented by restriction (1l). We ignore Kirchhoff's voltage laws since the majority of the system consist of high voltage direct current (HVDC) branches that are fully controllable, yielding a transport model with no loop flows as shown in Equation (1j) and (1k). However, linear losses for power flows f_b are incorporated to reflect both the transmission distance and the use of necessary voltage transformers and power electronics (1f).

The variability of wind, solar, hydropower, and load is incorporated using full-year hourly profiles from both historical and simulated weather data, where the latter source is particularly relevant for offshore locations with limited historical information (Kristiansen et al., 2016). We model the hourly variability of these resources using factors γ_{it} in (1h) ranging from 0 to 100% inflow/availability and multiplied by the maximum existing capacity, P_i^e, plus any additional capacity investments, x_i (1c). We use an agglomerative hierarchical clustering technique (Härtel et al., 2017a) in order to reduce the hourly resolution from 8760 hours to 500 representative ones, where each hour is weighted by ω_t (number of hours in a cluster) in (1c) and (1i), while maintaining multi-variate correlations between the different technologies and geographical coordinates.

Variables g_{it} denote generator dispatch levels with marginal cost MC_i and emission cost CO_2 for technologies that use fossil fuels. Load shedding, s_n , is allowed at a cost equivalent to the value of lost load $VOLL$. The market clearing, or energy balance, for each time step is given by Equation (1f) for a projected demand profile, D_{lt}. We determine long-run electricity prices from the dual variables of Equation (1f) after fixing all transmission investment variables (binaries) and resolving the remaining generation investment and dispatch problem that yields a linear program.

$$\min_{x,y,z,g,f,s} \quad IC + a \cdot OC \tag{1a}$$

where

$$IC = \sum_{b \in B}(C_b^{fix} y_b^{num} + C_b^{var} y_b^{cap}) + \sum_{n \in N} CZ_n z_n + \sum_{i \in G} CX_i x_i \tag{1b}$$

$$OC = \sum_{t \in T} \omega_t (\sum_{i \in G}(MC_i + CO2_i) g_{it} + \sum_{n \in N} VOLL s_{nt}) \tag{1c}$$

$$C_b^{fix} = B + B^d D_b + 2CS_b \qquad \forall b \in B \tag{1d}$$

$$C_b^{var} = B^{dp} D_b + 2CS_b^p \qquad \forall b \in B \tag{1e}$$

subject to

$$\sum_{i \in G_n} g_{it} + \sum_{b \in B_n^{in}} f_{bt}(1 - l_b) - \sum_{b \in B_n^{out}} f_{bt} + s_{nt} = \sum_{l \in L_n} D_{lt} \qquad \forall n, t \in N, T \tag{1f}$$

$$s_{nt} \leq \sum_{l \in L_n} D_{lt} \qquad \forall n, t \in N, T \tag{1g}$$

$$P_i^{min} \leq g_{it} \leq \gamma_{it}(P_i^e + x_i) \qquad \forall i, t \in G, T \tag{1h}$$

$$\sum_{t \in T} \omega_t g_{it} \leq E_i \qquad \forall i \in G \tag{1i}$$

$$-(P_b^e + y_b^{cap}) \leq f_{bt} \leq (P_b^e + y_b^{cap}) \qquad \forall b, t \in B, T \tag{1j}$$

$$y_b^{cap} \leq P_b^{n,max} y_b^{num} \qquad \forall b \in B \tag{1k}$$

$$\sum_{b \in B_n} y_b^{num} \leq M z_n \qquad \forall n \in N \tag{1l}$$

$$x_i, y_b^{cap}, g_{it}, s_{nt} \in \mathbb{R}^+, \quad f_{bt} \in \mathbb{R}, \quad y_b^{num} \in \mathbb{Z}^+, \quad z_n \in \{0, 1\}$$

8.2 Summary of input data

Table 6: Input data: Marginal costs, generation capacity and peak load per country (ENTSO-E, 2016). An emission tax of 76 €/tonCO_2 is added on top of marginal costs for thermal generators. The economic lifetime of investments is assumed to be 30 years and the discount rate is 5 %.

	Costs	NO	DK	DE	NL	BE	GB	Sum
	EUR/MWh	MW						
Biomass	50	0	1 720	9 340	5 080	2 500	8 420	26 880
Coal	21	0	410	14 940	0	0	0	15 350
Lignite	10	0	0	9 026	0	0	0	9 026
Natural Gas	65	855	3 746	45 059	14 438	10 040	40 726	114 864
Hydro	-	48 700	9	14 505	38	2 226	5 470	70 948
Nuclear	5	0	0	0	486	0	9 022	9 508
Oil	140	0	735	871	0	0	75	1 681
Solar PV	0	0	1 405	58 990	9 700	4 925	11 915	86 935
Wind Onshore	0	1 771	6 695	76 967	5 495	3 518	27 901	122 347
Wind Offshore	0	724	6 130	20 000	4 500	4 000	30 000	65 354
Total generator capacity	-	52 050	20 850	249 698	39 739	27 209	103 510	493 056
Peak load	-	24 468	6 623	81 369	18 751	13 486	59 578	204 275

8.3 Coalition formation of non-zero countries

Table 7 shows a subset of the $2^6 = 64$ possible coalitions that only includes countries with veto power, i.e. Norway (NO), Denmark (DK), Great Britain (GB), and Germany (DE).

Table 7: Coalition formation of non-zero players, in our case countries, from zero investments (0,0,0) to the cooperative solution (1,1,1) where all countries join the grand coalition.

Coalition	Lines built	Net benefits [bn€]
()	(0,0,0)	0.00
(DE)	(0,0,0)	0.00
(DK)	(0,0,0)	0.00
(GB)	(0,0,0)	0.00
(NO)	(0,0,0)	0.00
(DE,DK)	(0,0,0)	0.00
(DE,GB)	(0,0,0)	0.00
(DE,NO)	(0,1,0)	8.8
(DK,GB)	(0,0,1)	6.1
(DK,NO)	(0,0,0)	0.00
(GB,NO)	(1,0,0)	11.2
(DE,DK,GB)	(0,0,1)	6.1
(DE,DK,NO)	(0,1,0)	8.8
(DE,GB,NO)	(1,1,0)	19.1
(DK,GB,NO)	(1,0,1)	16.5
(DE,DK,GB,NO)	(1,1,1)	25.3

8.4 The core of the cooperative game

We denote x_i the allocation of net benefits that country i will receive from the development of transmission interconnections. The inequalities below define the core of the cooperative game for non-zero players or host countries.

Individual rationality constraints:

$$x_{DE} \geq 0 \quad x_{DK} \geq 0 \quad x_{GB} \geq 0 \quad x_{NO} \geq 0$$

Coalitional rationality constraints:

$$\begin{aligned}
x_{DE} + x_{DK} &\geq 0 \\
x_{DE} + x_{GB} &\geq 0 \\
x_{DE} + x_{NO} &\geq 8.8 \\
x_{DK} + x_{GB} &\geq 6.1 \\
x_{DK} + x_{NO} &\geq 0 \\
x_{GB} + x_{NO} &\geq 11.2 \\
x_{DE} + x_{DK} + x_{GB} &\geq 6.1 \\
x_{DE} + x_{DK} + x_{NO} &\geq 8.8 \\
x_{DE} + x_{GB} + x_{NO} &\geq 19.1 \\
x_{DK} + x_{GB} + x_{NO} &\geq 16.5
\end{aligned}$$

Collective rationality constraint:

$$x_{DE} + x_{DK} + x_{GB} + x_{NO} \geq 25.3$$

A candidate allocation rule x^* is stable if it satisfies all individual, coalitional, and collective rationality constraints.

8.5 Net benefits per country under conventional allocation schemes

Under both the ESP and the PNBD the final allocation of benefits are not part of the core of the cooperative game, as it was defined in Section 8.4. This is because both allocations violate the collective rationality constraints (defined excluding zero players), since third-party countries receive positive net benefits.

Table 8 supports the discussions in Section 6 about the potential stability of these allocation methods when the game is analyzed as a non-cooperative one. It illustrates that the two conventional allocation schemes do, in fact, result in Nash equilibria for our case study in a non-cooperative setting. Note that if, under any of these two mechanisms, countries agree to support the three interconnections (1,1,1), then no country would have incentives to unilaterally block a transmission project. However, note that this is also true for other project portfolios, which makes prediction using concepts from non-cooperative game theory very difficult.

Table 8: Relative net benefits [m€] with respect to the grand coalition (1,1,1). Left side shows the result from an Equal Share cost allocation, while the right part comprise a Positive Net Benefit Differential allocation of costs. The combinations have the following ordering (NorthSeaLink, NordLink, Viking). The most beneficial projects are those with the highest numbers (bold font).

	ESP						**PNBD**					
	NO	DE	DK	BE	NL	GB	NO	DE	DK	BE	NL	GB
(0, 0, 0)	-9 414	-3 202	-1 773	-180	-73	-10 670	-8 679	-3 917	-2 822	-180	-73	-9 641
(0, 0, 1)	-9 402	-2 979	**80**	-158	-77	-6 629	-8 666	-3 694	-601	-158	-77	-5 968
(0, 1, 0)	-3 591	-436	-1 783	-87	-42	-10 591	-3 161	-846	-2 832	-87	-42	-9 563
(0, 1, 1)	-3 578	-71	65	-66	-7	-6 679	-3 377	-644	-519	-66	-7	-5 724
(1, 0, 0)	-5 393	-3 132	-1 768	-117	-89	-3 628	-4 363	-3 847	-2 816	-117	-89	-2 894
(1, 0, 1)	-5 288	-3 016	-17	-63	-32	-8	-4 343	-3 731	-264	-63	-32	-405
(1, 1, 0)	**44**	-382	-1 791	-23	-43	-3 623	**46**	-501	-2 840	-23	-43	-2 845
(1, 1, 1)	0	**0**	0	**0**	**0**	**0**	0	**0**	**0**	**0**	**0**	**0**

Paper I

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Combining optimization and tradespace exploration to gain insights for decision support in power system expansion planning

Martin Kristiansen[a], Carl Fredrik Rehn[a], Stein-Erik Fleten[a], Magnus Korpås[a], Benjamin F. Hobbs[b]*

[a]*Norwegian University of Science and Technology (NTNU), Trondheim, Norway*

[b]*The Johns Hopkins University, Baltimore, Maryland, USA*

Abstract

This paper introduces a set of methods from the systems engineering community to an increasingly complex problem in the optimization literature, namely transmission expansion planning (TEP). A majority of conventional TEP models relies on "black-box" optimization programs, minimizing system costs or maximizing welfare. Although multiple objectives can be incorporated into those models, or different versions of it, it is often difficult for decision makers to understand the model and extract insights on the main value tradeoffs. To aid with this problem, we leverage techniques such as multi-attribute tradespace exploration and multi-epoch analysis to systematically untangle problem complexities and help gain valuable insights. In combination with an optimization program that co-optimize capacity expansion investments and power market operation, we investigate different high-level solutions of the future North Sea Offshore Grid. Our case study comprise multinational stakeholders and serves as a good example for similar multi-stakeholder planning problems. The results demonstrate that the combination of optimization and tradespace exploration yields significant value to the traditional decision support framework for TEP. Moreover, it clearly illustrates that by leveraging this multidisciplinary, generic framework, one could help decision makers to better understand and communicate complex problems, such as TEP, as well as its potential system impact subject to uncertainty. Exploiting this powerful combination could help to eliminate subjective utility interpretations and thus provide more efficient decision support due to increased knowledge and insights about the problem at hand.

Keywords: Decision Support; Optimization; Systems Engineering; Tradespace Exploration; Transmission Expansion Planning.

1. Introduction

Nearly €150bn worth of pan-European infrastructure investments are needed the coming decade in order to provide a reliable power system that complies with energy- and environmental targets, given current projections on supply and demand (ENTSO-E, 2016). This demonstrates the importance of adequate decision support tools for long-term power system planning and operation, which has driven an increasing application of Operations Research to this field. Planning for infrastructure investments, i.e. transmission expansion planning (TEP), is becoming increasingly complex due to large-scale integration of renewable power generation, a changing political and regulatory landscape, and technological advancements (Gorenstein Dedecca and Hakvoort, 2016; Lumbreras and Ramos, 2016). This has led to a large and complex *system-of-systems*, e.g. electrification of transport sector relates to power systems and vice versa, changing the market characteristics and demanding more operational- and managerial flexibility than ever before (Cochran et al., 2014; Hobbs et al., 2016). Moreover, as the geographical scope of modern TEP comprise *multiple countries and stakeholders* with varying objectives it becomes challenging to uncover mutually agreeable solutions

(Huppmann and Egerer, 2015; Konstantelos et al., 2017). Consequently, this might create difficulties in reaching the most efficient investment strategies for the system as a whole towards targets for the greater good (Egerer et al., 2013; Kristiansen et al., 2017) – on security of supply, efficiency, and reduced greenhouse gas (GHG) emissions (EU Commission, 2011).

Traditional TEP models are often formulated as single-objective "*black box*" optimization programs calculating one, or a few, "optimal" solution(s) as shown in e.g. (Sullivan, 1977) and more recently (Hobbs et al., 2016; Lumbreras and Ramos, 2016). This is a powerful approach in terms of simulating a physical system with multiple operational decision variables (potentially millions), but it tends to provide *little insight* for investment decision support in the end, as you will be left with one, or a handful, of solution(s) bounding your knowledge about *alternatives and tradeoffs* (Simon, 1996). Although the traditional "black-box" operations research framework for TEP can incorporate multiple objectives by, for instance, penalizing the systems inability to cover electricity demand or pricing the social costs of greenhouse gas (GHG) emissions (Hemmati et al., 2013; Lumbreras and Ramos, 2016), it still falls short in terms of insight generation regarding the tradeoffs between those attributes.

Tradeoffs in TEP become even more difficult to understand when incorporating uncertainty (Velasquez et al., 2016). A sensitivity analysis might provide decision makers with a mapping of the potential solution space, but it lacks the ability of providing robust decision support (Higle and Wallace, 2003) – i.e. decisions that are expected to perform good over all possible scenarios. However, robust optimization (Mínguez and García-Bertrand, 2016; Ruiz and Conejo, 2015) and stochastic programming (Munoz et al., 2014, 2016; van der Weijde and Hobbs, 2012) allows for endogenous incorporation of uncertainty yielding robust decisions. The latter could also be done in a multi-stage fashion in order to capture the value of the option to postpone decisions (Huang and Ahmed, 2009; Pflug and Pichler, 2014).

On multi-objective optimization for TEP, there is a rich amount of literature based on heuristics searching Pareto-optimal solutions. For instance, a stochastic framework for TEP is presented in (Arabali et al., 2014) by considering three objectives utilizing a decision-making process to assess a set of Pareto optimal solutions that are non-dominant with respect to all three objectives. A similar approach is presented in (Wang et al., 2008) by using a congestion index to measure the degree of congestion at a transmission line, in addition to the two other objectives; investment costs and power outage costs. The latter authors use improved strength Pareto evolutionary algorithm (SPEA) to solve the multi-objective TEP model, followed by a Euclidean distance ranking method for decision making within the given Pareto-optimal set.

Applications of multi-attribute utility theory (MAUT) and multiple criteria decision making (MCDM) dates back to (Cohon and Marks, 1975), (Belton and Stewart, 2002) and partly also for some TEP applications (Püttgen, 1977; Sullivan, 1977). For instance, Cohon used the terms tradespace and multi-objective programming already in the mid-70s, communicating the added value in terms of insights and particularly for public planning problems (Cohon, 2013). More recently, (Torre et al., 1999) show how decision analysis can be used in combination with TEP to produce more robust investment strategies that represent a better hedge against future uncertainties. Voropai and Ivanova (Voropai and Ivanova, 2002) look at multi criteria electric power system expansion based on the fundamental concepts of MAUT and MCDM. The underlying philosophy of those multi objective approaches is somewhat similar to the multi-attribute tradespace exploration (MATE) presented later in this paper (Ross et al. 2002; Ross, Hastings, and Diller 2003), with respect to evaluating Pareto and fuzzy-Pareto front solutions. However, the reviewed literature does not cope with the use of concepts from systems engineering, although the term tradeoff analysis was slightly introduced for evaluating renewable generation in (Connors, 1996).

The concept of MATE is frequently used in methods developed at MIT over the past decades, which are largely synthesized into an overall framework for system design called the Responsive System Comparison (RSC) method (Ross et al. 2008, 2009). As the general focus is on how to design and manage complex systems, the field is highly applicable for addressing problems related to TEP comprising *multiple- and variable objectives* (de Weck, Roos, and Magee 2011). In particular, we believe the method can help decision makers to gain insight by untangling system complexities and by exploring decision alternatives in different contexts and needs, using methods such as MATE and epoch-era analyses (EEA).

In this paper, we present a generic framework on how to combine traditional optimization program for TEP with the aforementioned methods from the systems engineering community. This allows us to bridge the gap between classical problem structuring (Belton and Stewart, 2010; Keeney, 2009), i.e. carefully defining the problem at hand and thinking about what objectives that really matters (Keeney, 1982, 1996), and in the end defining tradeoffs (Cohon, 2013) and valuating them against each other (Belton and Stewart, 2002) in a tradespace. Although this is a rather philosophical process, we focus on how to use an optimization model to generate a tradespace and discuss aspects that could serve as an important basis for insight generation and assessment of utility functions (Brown, 1984). That is, presenting a constructive approach that could help model developers and analysts to communicate with decision makers and help them think about, and form, priorities of what want to, and can, achieve. Moreover, we apply this framework with a case study considering capacity expansion of three offshore transmission corridors in the North Sea Offshore Grid (NSOG), comparing the added value with traditional single-objective, optimization models.

2. Methodology

In this section, we present the responsive system comparison (RSC) method as a generalized framework for system design. Thereafter, we go through some of the tools for capturing value, structuring problems and exploring alternative solutions.

2.1. The Responsive System Comparison method

The RSC method is a generic method for system design, with the purpose of taking “a designer or system analyst (RSC practitioner) through a step-by-step process of designing and evaluating dynamically relevant system concepts” (Ross et al., 2009). Originally, the RSC method was presented in (Ross et al. 2008, 2009), with updated references being (Pettersen et al. 2017; Schaffner, Ross, and Rhodes 2014) refining the procedure for this step-wise approach (Figure 1).

The method comprises nine steps, grouped into three modules, as illustrated in Figure 1. “Information gathering” is the first module, where the value-driving context and value-driven design alternatives are defined, and the epochs are characterized. Epochs represent periods with constant context and needs, meaning that objectives and exogenous variables will remain the same. For TEP applications, this would be translated into a spatial and temporal mix of supply and demand for a given system, or other potential epoch variables such as a CO_2 price.

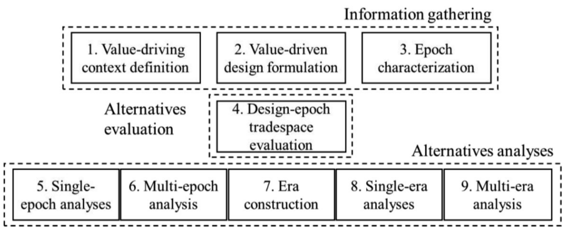

Figure 1 - The responsive system comparison (RSC) method, a generalized method for system design (Pettersen et al., 2017).

In the second module, the "alternatives evaluation", the mapping process between the design alternatives, the epochs and the value attributes is performed. That is, a TEP model that enables system design and analyses is determined. Even though the whole process represents system design overall, this step connects the form and function domains in a mapping process – which can be considered as the definition of system design (Suh, 1990). The second module can thus be thought of as the mapping process from a discretized space of decision variables to a tradespace.

In the third module, the "alternative analyses", the system design analyses are pursued. Multiple analyses can be performed, depending on the characteristics of the problem. Design alternatives can be analysed in single epochs, or across multiple epochs. For instance, single-epoch analyses can be assessed for individual TEP problems with fixed contexts and needs, while multi-epoch analyses are more suitable for uncertainty regarding contexts and needs. Note that multiple epochs can be defined for a certain point in time, e.g. four different epochs for year 2030, or it can be defined for multiple time steps such as for year 2030, 2035, 2040, and 2045. The latter combination of epochs yields something referred to as "eras" which enable analyses of temporal character. That is, multi-era analyses of a system with changing contexts and needs over time.

2.2. Key aspects of the RSC method for transmission expansion planning

The RSC method is a generalized approach that helps the practitioners to structure complex design problems, and can in theory be collapsed into most system design analyses. The method helps the practitioners to think about interesting aspects, such as who are the stakeholders and what do they care about? What is considered as value and how can potential external factors affect the system's ability to deliver value? The method primarily takes a discretized approach to design alternatives, analogous to set based design, allowing the decision makers more easily explore potential solutions and understand their performance in different epochs. The overall approach to this method can be broken into three parts in line with the blocks in Figure 1, namely i) evaluation of design alternatives, ii) tradespace exploration, and iii), epoch-era analyses. The following subsections will describe those three pillars in detail.

2.2.1. Evaluation of design alternatives – *what is value?*

Clearly determining the value, or objectives, is essential in terms of finding good solutions. However, this part may be very difficult to do with high precision or optimality. For example, how should we aggregate the efficiency, reliability, security, and eco-friendliness of a TEP solution into one overall score, in what unit should this score be, and how should we discount to get present values? Traditional TEP problems take a monetary approach in line with microeconomics, where the interest is to maximize welfare, by internalizing externalities by adding e.g. CO_2 tax and a penalty cost per hour of downtime known as “the value of lost load” (VOLL). Thus, the individual components of the multi-attribute value function are all monetary, and can be summarized. An alternative approach can be to transform the value attributes, e.g. efficiency or reliability, to a utility function representing the preferences to the relevant stakeholder, or multiple stakeholders (Fitzgerald and Ross, 2016), in line with multi-attribute utility theory (Keeney and Raiffa, 1993). However, each of these approaches need a proper representation of the constituent attributes, and a proper insight on how to discount future values to trade them off against the short term. In this paper, we will use the traditional monetary welfare object function aggregation for the TEP model (defined in second module in Figure 1), in order to simplify and be consistent with the optimization approach for final comparisons. However, we will also measure performance in multiple attributes, although this is not part of the objective function itself, such as utilization of renewables, reduction in GHG emissions, and security of supply.

2.2.2. Tradespace exploration – *optimization vs. exploration*

Optimization programs requires a well-defined representation of the problem, but for opaque problems this may not exist. Thus, instead of optimizing an oversimplified and incorrect representation of reality to find *“the best”* solution, it can be valuable to explore multiple solutions and try to gain insights about the problem and alternative solutions. This accounts both for analysts and management decision-makers, not to mention for communicative purposes between them and other stakeholders involved in a project. Such exploration draws a parallel to set based design (Singer et al., 2009), as in that multiple solutions are assessed at the same time and options are kept open before specifications and tradeoffs are more fully understood. In general, we want to explore the main tradeoff between value and costs - i.e. what can we get from our resources invested? Furthermore, what are the tradeoffs between the competing value attributes at a given overall system cost? These questions are addressed in research on MATE (Ross et al. 2002; Ross, Hastings, and Diller 2003).

A tradespace is simply the space of trades, i.e. the space of possible design alternatives (Ross and Hastings, 2005). A tradespace plot is thus a scatterplot of a discretization of the design space. To more easily gain insights we make use of interactive visualizations, primarily adapted from (Curry et al., 2017; Curry and Ross, 2015). The interactive plot allows the user to explore the solution space and learn insights. For instance, one could use such a plot to filter out desirable ranges of one or more value attributes and trace those criteria back to a given set of design alternatives, and subsequently choose one design with the most appealing tradeoffs. The latter could be useful if the decision makers wants to explore their alternatives given a range of pre-defined performance targets in e.g. GHG emissions reductions.

2.2.3. Epoch-Era Analyses – *changing context and needs*

To more flexibly use scenarios in exploratory design analyses, the epoch-era framework was developed (Ross and Rhodes, 2008). Epoch-era analyses branches into two subgroups; epoch analyses and era analyses. The epoch representations are particularly useful for tradespace exploration, as we can explore sets of alternative designs in specific epochs with given context and needs, analogous to the short-term in microeconomics (Varian, 2006). However, in the long-term, both context and needs can change. Eras represent the long-term, and are constructed by chains of epochs. Eras could thus be thought of as stages in a temporal scenario tree (Pflug and Pichler, 2014), allowing us to analyse lifecycle performance of systems.

For instance, a tradespace can be simulated for a given epoch, yielding the basis for single-epoch analysis. However, this will only create insights to the designs' performance for one particular epoch. In order to account for uncertainty one could augment single-epoch to multi-epoch analyses by assessing the performance of certain designs over multiple epochs. The latter would be an appropriate approach if you are evaluating something in the future where contexts and needs are uncertain, e.g. as in the forthcoming case study of year 2030.

3. Case Study – Transmission Expansion Planning in the North Sea

A case study for transmission expansion planning (TEP) of the North Sea Offshore Grid (NSOG) using the responsive system comparison method (RSC) is here presented. We choose the NSOG as a proper case study as it is identified as one of the strategic infrastructure (ENTSO-E, 2016; EU Commission, 2015) projects in Europe since it serves the two-fold purpose of both integrating offshore wind resources (Van Hulle et al., 2009) as well as interconnecting countries for cross-border trade (Egerer et al., 2013; Strbac et al., 2014). For more information regarding models and case studies on the NSOG, please consult (Gorenstein Dedecca et al., 2017; Gorenstein Dedecca and Hakvoort, 2016; Konstantelos et al., 2017; Kristiansen et al., 2017). The following sections present the case study in context of the RSC method using multi-attribute tradespace exploration (MATE) and epoch-era analyses (EEA).

3.1. Information gathering – Problem identification

This subsection discusses Step 1 in Figure 1 in context of the case study. That is, defining what values we care about when building an electricity infrastructure in general and particularly in the North Sea area. The following two steps in Figure 1 are discussed in the subsequent subsections.

3.1.1. Value driving context definition

In general, the TEP problem arises from an increase in demand for energy, particularly in terms of electricity consumption as more appliances and cars are based on this technology. Consequently, sufficient grid infrastructure is in many cases essential due to spatial and temporal imbalance in production and consumption, especially with increasing supply capacities from variable renewable energy sources (VRES) due to weather dependencies. The main goal for TEP is in most cases to make investment decisions for grid expansion in order to achieve a cost-efficient operation of the system today, and in the future. The purpose of such a system can be to increase the standards of living, empower economic growth, increase security of energy supply, or contribute to enhancing other systems by e.g. producing aluminium for cars. Even though the purpose of a system can be diverse and difficult to quantify, it becomes even more complicated as one starts to look at externalities in other systems, such as GHG emissions' impact the world's climate and environment. The latter might yield feedback to what a decision maker must consider when planning several years ahead (see illustrations in Figure 2), and it is therefore important to carefully evaluate what we really want to achieve and how it is quantified.

Figure 2 illustrates the system boundaries for our case study comprising six countries, namely; Norway (NO), Denmark (DK), Germany (DE), Belgium (BE), The Netherlands (NL) and Great Britain (GB). Supply and demand for electricity can be matched locally, i.e. within individual countries, or be transferred cross-border between different countries through a multinational grid infrastructure. The performance of this system might yield feedback to epoch variables

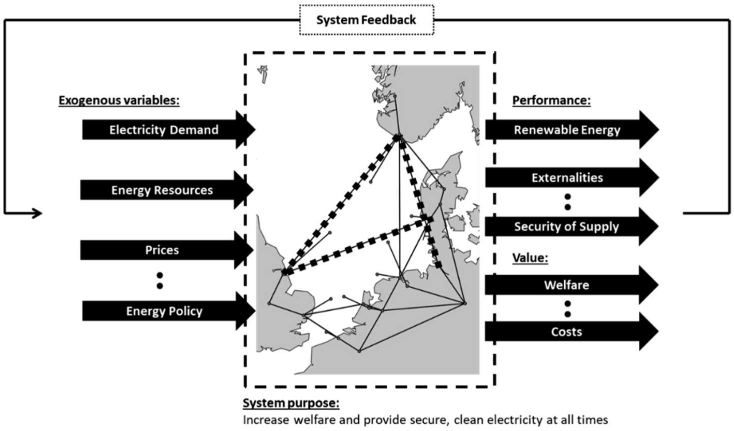

Figure 2 - Illustration of case study system boundaries. For a given context and needs (epoch), different system designs are evaluated based on expected performance and values. The dotted lines between the countries represent decision variables (transmission corridors to expand) while the solid lines represent already existing corridors with fixed capacity.

used in the decision making process, as discussed in previous paragraph. We focus on the three value attributes outlined by the EU Commission (EU Commission, 2011) for the grid system defined; i) efficient operation, ii) security of electricity supply, and iii) utilization of renewable energy sources to reduce GHG emissions. That is, the overall objectives are for the "greater good" stakeholder and the system as a whole. Thus, we can synthesize the outcome of Step 1 in Figure 1 to the following value proposition: *Providing a grid infrastructure in the North Sea for cost-efficient utilization of multinational resources, increased security of supply, and reduced GHG emissions.* This is in line with the EU Commissions' objectives.

Table 1 – System value attributes – in line with the EU Commissions' objectives (EU Commission, 2011).

Value attribute	Units	Lower bound	Upper bound	Description
Cost-efficiency	€	-	-	High system welfare and low operational cost.
Security of supply	-	0	1	Ensure a certain margin on net supply capacity.
Emission reductions	-	0	1	Utilize environmental friendly resources.

3.1.2. Value-driven design formulation

Table 1 presents the value attributes from the discussion in 3.1.1, i.e. what we chose to care about when exploring alternative designs. These include cost-efficient operations, security of supply and decarbonisation (i.e. reduction of GHG emissions). Each performance attribute should carefully be determined in terms of units and lower- and upper bounds with respect to their utility, or performance. This makes it easier to weight them into one aggregated utility function. However, note that we do not aggregate into one objective function in this paper – we only measure their performance as a result of maximizing welfare.

Efficiency (Table 1) relates to cost-efficient investments and operations of a system that meets current and future demand for electricity. Security is a measure of a system's ability to serve demand at all times, which in many cases is quantified as the Loss of Load Expectations (LOLE) or Expected Energy Not Served (EENS) (Koldingsnes, 2017). However, as we look at the security issue from a multinational perspective we choose to approximate the measure of security of supply by taking the load-weighted average of net generated energy, relative to its maximum potential. This means that both the impact of new transmission corridor expansions and utilization of renewables are implicitly taken into consideration. Finally, emission reductions are simply a measure on the impact of higher utilization of clean VRES, leading to lower GHG emissions in the system due to an efficient spatial- and temporal utilization of the latter.

Table 2 - Design variables for the North Sea offshore grid comprising three transmission corridors.

Design variable	Units	Values
Corridor 1 (NO-GB)	MW	0, 500, …, 5500
Corridor 2 (NO-DE)	MW	0, 500, …, 5500
Corridor 3 (DK-GB)	MW	0, 500, …, 5500

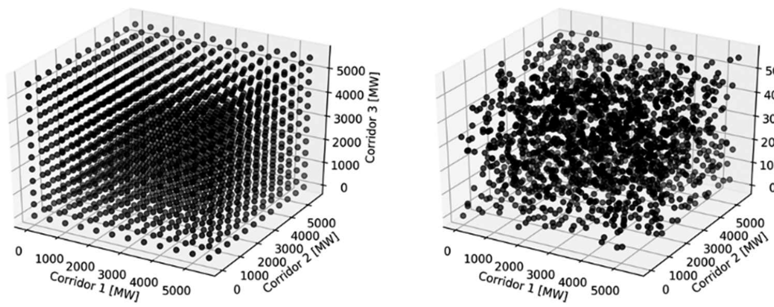

Figure 3 - Illustration of how design variables, and combinations of them, are discretized to map the resulting tradespace with a TEP model. Left plot shows a combinatorial approach, while the right plot uses Latin hypercube sampling.

Note that these value attributes can be affected in multiple ways. For instance, one could take actions at the demand-, supply-, or infrastructure side, which all are interlinked. In this paper, we focus on infrastructure designs only, as indicated with the system boundary illustrations in Figure 2. The design variables listed in Table 2 does therefore relate to infrastructure expansion at the three indicated transmission corridors; Corridor 1 (NO-GB), 2 (NO-DE), and 3 (DK-GB) as illustrated by the dotted lines in Figure 2. Their units and possible values are listed in Table 2. In our case, each corridor is discretised into 12 different capacities ranging from 0 MW to 5500 MW, with 500 MW step length, resulting in 12^3 (1728) different design alternatives. Figure 3 illustrates this discretization of design variables, where the left plot uses a combinatorial approach and the right plot a Latin hypercube sampling (Stein, 1987). We use the combinatorial approach. Computationally, this means that the TEP optimization model must be executed 1728 times in order evaluate and map the complete tradespace for all possible combinations for design variables. However, note that this can easily be parallelized and that the resulting optimization programs are linear since the investment variables are fixed, which means that each model instance can be solved faster than if investment variables were determined endogenously. In our case, the total calculation time was 6912 seconds (almost 2 hours) with a standard Intel i7 2.80 GHz laptop excluding parallelization.

Table 3 - Epoch variables. Values are given by ENTSO-E's four 2030 scenarios (ENTSO-E, 2016) referred to as Vision 1 - 4.

Epoch variable	Unit	Values
CO_2 price	€/tonCO_2	17 - 76
Thermal supply	GW	137 - 150
Renewable supply	GW	270 - 392
Peak demand	GW	191 - 209

Table 4 - Four potential epochs in year 2030 to consider. The values (ENTSO-E, 2016) are given in system aggregate quantities.

Epoch name	Slow Progress	Money Rules	Green Transition	Green Revolution
Epoch ID	1	2	3	4
CO_2 price [€/tonCO_2]	17	17	71	76
Thermal capacity [GW]	150	137	142	141
Renewable capacity [GW]	270	284	392	382
Peak demand [GW]	209	191	206	204

3.1.3. Epoch characterization

The operation of a power system is highly dependent on exogenous parameters that are subject to uncertainty in the long-term. Examples include, but is not limited to, fossil fuel prices, CO_2 price on emissions, supply capacity mix, demand and capital costs. All those can have a considerable impact on the system's ability to provide the desired performance or utility. For this study, we choose to focus on four different epoch variables to incorporate different scenarios for "context and needs" in the future, albeit here focusing only on changes in context. The epoch variables are listed in Table 3 with corresponding units and value ranges using data from ENTSO-E for year 2030 (ENTSO-E, 2016). Note that thermal- and renewable capacity together represent the aggregated supply side, but we use this grouping since their characteristics is quite diverse in terms of availability and GHG emissions. Thermal relates to everything with CO_2 emissions from electricity generation, while our renewable classification refers to everything else, including e.g. nuclear.

Each epoch variable is quantified in four different epochs. We refer to scenarios that are generated by ENTSO-E as different transit-states towards the EU Commission's climate- and energy targets for 2050 *(ENTSO-E, 2016)* ranging from "slow progress" (Epoch 1) to "green revolution" (Epoch 4), as shown in Table 4. These epoch variables are used to perform single-epoch and multi-epoch analyses later in this case study.

3.2. Alternatives evaluation – using a transmission expansion planning model

In order to evaluate the performance of a design for a given epoch, we make use of a TEP model (Kristiansen et al., 2017). This is an optimization model formulated as a mixed-integer linear program (MILP) that co-optimizes the net present value of grid investments and market operation, i.e. the cost of electricity supply to consumers for a given epoch. The system's ability to cope with variable generation, such as solar PV and wind, is valued by incorporating multiple hours of a year. To this end, the system must manage both intraday and seasonal variability. Moreover, the market simulations are assumed to take place in a perfectly competitive environment with price-inelastic consumers. The resulting optimization program is shown in Equations (1a)-(1l) in the Appendix, in addition to the general notations that are used in the model. For more detailed information, please consult (Kristiansen et al., 2017).

The optimization model is used to evaluate a set of design alternatives. Note that the optimization model itself can find an "optimal solution" for a given epoch, or scenario. However, to generate more insight in terms of alternative investment strategies and tradeoffs, we use the optimization model to simulate and evaluate different design alternatives which were illustrated in Figure 3. This allows us to visually map the solution space, which we refer to as the tradespace. The next section will demonstrate the visual insights gained by using this approach, as well as comparing it with traditional "black-box" optimization.

3.3. Alternatives analyses – exploring alternatives and tradeoffs

The following subsections will present single-epoch MATE analysis of Epoch 1, followed by a multi-epoch comparison of all four epochs and ways to analyse them using the fuzzy Normalized Pareto Trace (fNPT) metric.

3.3.1. Single-epoch analysis

A tradespace of the design alternatives in Epoch 1 is shown in Figure 4. The figure shows a snapshot of an interactive plot (Curry and Ross, 2015) that allows decision makers to visualize tradeoffs in system performance and investment costs in four dimensions; vertical- and horizontal axis, in addition to size and colour of the scatter plot. Each design alternative can be traced in the lower part of the figure, where information about its design dependencies, performance, and value attributes are mapped for one, or a group of, selected alternatives. Note that the value attributes in Figure 4 are broken into performance- and value attributes, in comparison to the three value attributes listed in Table 1. This is to make it more illustrative. For clarity, the value attributes efficiency, security and emissions reductions from Table 1 can be mapped to net welfare (added value on system level), security, and emissions reduction, respectively (Figure 4).

The diameter of the dots in Figure 4 indicates the level of security of supply. MATE shows that high levels of security can be achieved at relatively low investment costs, as its impact from Corridor 2 is limited – i.e. Corridor 1 and 3 are more important if we care the most about security of supply. This is even more clear in Figure 5 where we have filtered out all designs that yield high security of supply, where the resulting alternatives traces back to low investment levels at Corridor 2 (NO-DE). The colour of the dots in Figure 4 indicates the level of emission reduction in million tonne CO_2, with darker colours representing the highest decrease in CO_2 emissions. If we filter out the alternatives with the highest emission reductions, we see the contrary effect that Corridor 2 plays the most important role and Corridor 3 becomes the least attractive one. This could be since the capacity mix between GB, NO, and DE is more flexible than the combination GB, NO, and DK – hence the ability to level out the necessary peak generation capacity from e.g. gas. The CO_2 price in Epoch 1 is 17€/ton, which shifts both coal and gas at higher marginal costs than zero-emitting technologies in the so called "merit-order" supply curve.

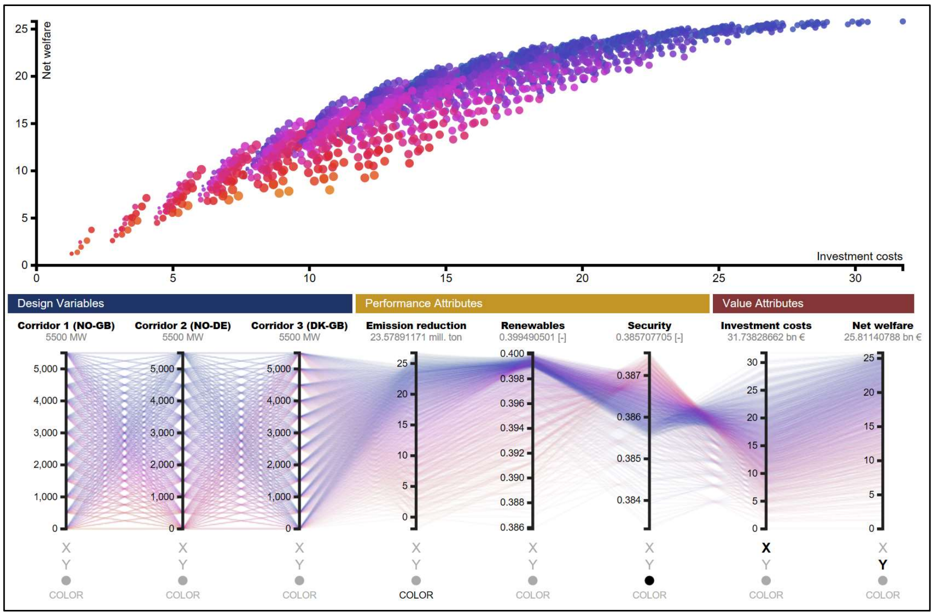

Figure 4 - Interactive tradespace visualization for context variables (Epoch 1). The lower part is a "trace map" for individual or a group of designs. The interactive plot is adapted from (Curry and Ross, 2015).

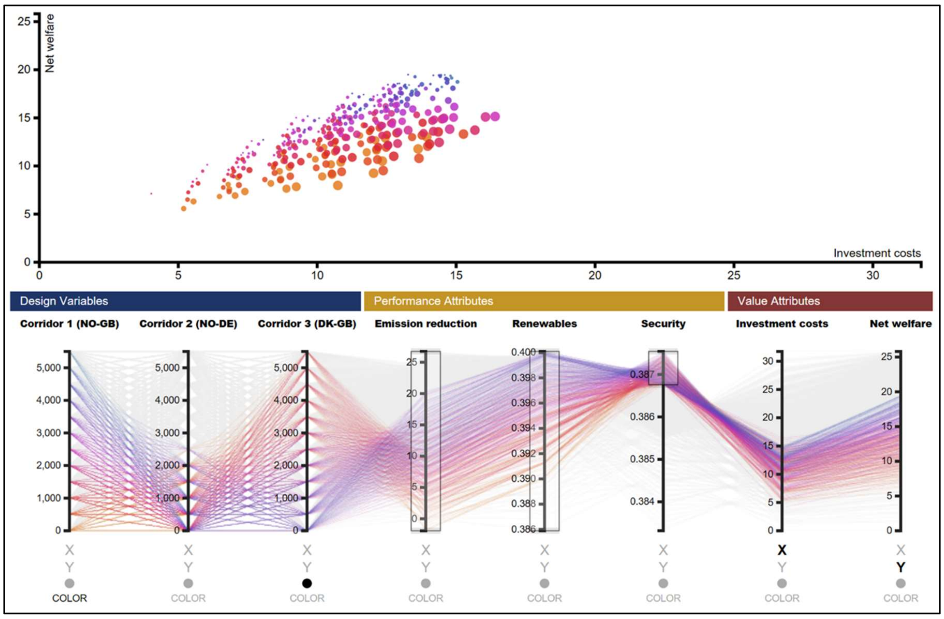

Figure 5 - Interactive tradespace visualization (Epoch 1) with a filtering of solutions yielding the highest security of supply. The interactive plot is adapted from (Curry and Ross, 2015).

Table 5 - fuzzy Normalized Pareto Trace (fNPT) for five possible solutions at k% fuzziness equal to 0%, 2% and 5%. Optimal 1-4 represent the optimal design vectors from the TEP model for corresponding epochs, while multi-epoch designs represent design vectors that are within a pre-defined k% fuzzy Pareto front in all epochs.

Design	Design vector [corridor 1,2,3]	fNPT 0%	fNPT 2%	fNPT 5%
Optimal 1	[4000,3000,0]	0.50	0.50	0.50
Optimal 2	[3000,4000,0]	0.50	0.50	1.00
Optimal 3	[3000,5000,3000]	1.00	1.00	1.00
Optimal 4	[4000,5500,2000]	0.25	0.75	1.00
Multi-epoch (k=0%)	[3000,5000,2000]	1.00	1.00	1.00
Multi-epoch (k=2%)	[1000,4000,1000]	0.50	1.00	1.00
Multi-epoch (k=5%)	[1000,1500,1000]	0.00	0.50	1.00

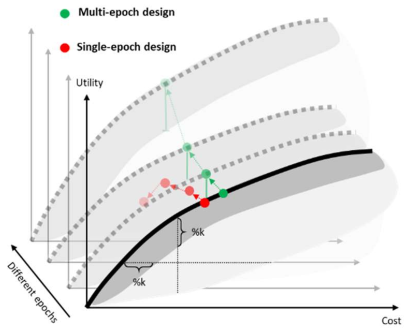

Figure 6 - Multi-epoch illustration of a design that performs well in one epoch (red) and another with robust performance over all epochs (green). The green design should preferably yield a utility within the k% fuzzy Pareto front (green error bars).

3.3.2. Multi-epoch analyses

Figure 6 illustrates the concept of fuzzy Normalized Pareto Trace (fNPT) which is used to identify certain designs that performs at the k% fuzzy Pareto front in multiple epochs (green dots), compared to single epoch optimal designs (red dots). The k%, as indicated in Figure 6, determines the size of the fuzzy Pareto front. For instance, k=0% represents the true Pareto front, while k=2% allows for 2% deviation from the true Pareto front in relative size of the tradespace. The fNPT is a measure of how often one particular design is within this predefined k% fuzziness Pareto front, where fNPT=1 means that the design in question is at the fuzzy Pareto front in all epochs considered. Contrary, if fNPT=0 the design does not occur at the k% fuzzy Pareto front in any of the considered epochs. For instance, a solution that performs well in Epoch 1 might not perform as good in e.g. Epoch 4, so the fNPT might be 0.5 since the design lays at the fuzzy Pareto front in only half of the epochs. Thus, we want to find designs with a small k% as possible and high fNPT.

Table 5 summarizes some good design alternatives identified, with corresponding fNPT for 0%, 2% and 5% fuzziness. First, consider the "optimal solution" calculated by the TEP model for Epoch 1 labelled "Optimal 1" in Table 5. This design vector occurs at the k% fuzzy Pareto front in 50% of the considered epochs, independent on the three considered levels of fuzziness. Second, the optimal solution for Epoch 4 is within the fuzzy Pareto front in 100% of the considered epochs when the fuzziness is 5%, but only in one (25%) of the epochs when the fuzziness is 0% - which makes since as it is the optimal solution for this particular epoch. Finally, note that the design labelled "Multi-epoch (k=0%)" occurs at the true Pareto front for all epochs. This multi-epoch design would be equivalent to the designs illustrated by the green dots in Figure 6 and Figure 7, with the latter figure summarizing the tradespaces for all four epochs.

The red dots in Figure 7 labelled with the number 1-4 represent design alternatives calculated by the TEP optimization model. Note that the red dot "1" performs slightly worse in Epoch 2, compared with red dot "2", at the magnitude of -1.88% worse than the optimal Epoch 2 design correcting for investment costs. In addition, the Epoch 1 design (red dot "1") is even worse performing in Epoch 4, leading to a potential loss of -2.21% compared with the optimal Epoch 4 design (red dot "4"). This is clearly shown in Figure 7 where the Epoch 1 design lays outside the 2% fuzzy Pareto front (green dots) in Epoch 4.

The aforementioned example demonstrates that some design alternatives might be more *value robust* than others when considering multiple epochs. The green dots in Figure 7 represent design alternatives that lie within the 2% fuzzy Pareto front for all epochs, which are those in Table 5 with fNPT equal to one in the "fNPT 2%" column. Notice that the density of those robust designs (green dots) are either located at very low- or high investment costs. That is, lower investment levels will always perform poorly and higher investment levels will often perform good. However, finding robust designs at the "elbow point" of the Pareto front seems to be harder due to lower density of the green dots. This is particularly true for Epoch 3 and 4 with high shares of variable generation capacity. Hence, there are limited robust solutions near the threshold for diminishing returns, in relative terms, and especially for instances with high shares of variability and corresponding need for flexibility (grid investments).

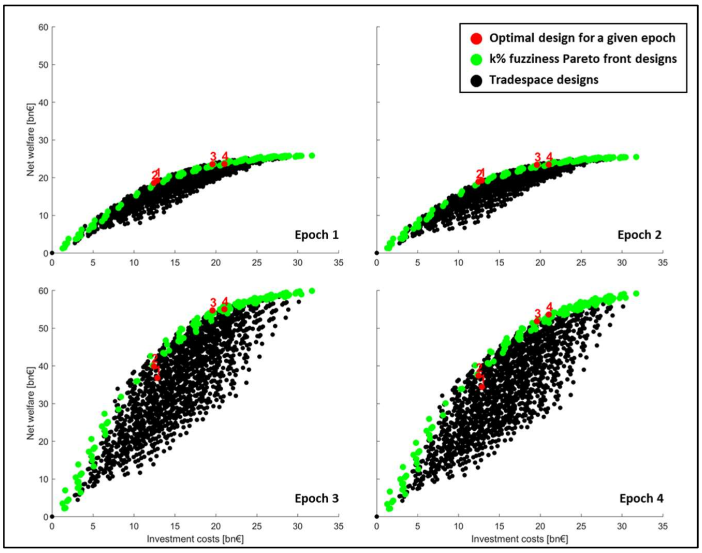

Figure 7 - Tradespace exploration for all epochs, i.e. Vision 1 – 4. Black dots comprise the total tradespace, while green dots represent designs that are within the 2% fuzzy Pareto front. The four red dots show "optimal designs" calculated by the optimization program with a labeled numbering from 1 – 4, indicating which epoch it is calculated for.

4. Discussion

At the more ambitious end of the considered epochs (Epoch 4) a more sporadic tradeoff pattern is observed, meaning that there seems to be a larger variation in welfare for a given level of investment costs – spanning over €60bn in system welfare, compared to €25bn in Epoch 1. One reason is the high levels of renewables in Epoch 4 (see Table 4), representing more variability in the system dispatch. Another reason could be the asymmetric allocation of low-cost renewable sources, with a majority located in GB and DE, where an incremental increase in transmission capacity could lead to more efficient use of those sources (analogous to lower operating costs). Moreover, for the same level of investment costs, compared with Epoch 1 (and 2), more value can be added to the system with the right combination of design alternatives. Hence, there is reason to believe that this space of tradeoffs represent a more complex problem – in terms of finding the right, robust design. This is useful insight for a model developer in terms of being aware of the value of capturing these complexities.

Regarding conflicting objectives, a filtering of solutions with a relative high level of security in Epoch 1 (Figure 5) traces back to high investment levels in Corridor 1 and 3, while Corridor 2 seems to be less important with investment levels close to zero. Contrary, filtering of solutions yielding high emission reductions results in higher investment levels for Corridor 2 and less investments at Corridor 1 and 3. This demonstrates valuable insights that can be gained by using this interactive plotting capability with graphical tracing back to design variables (i.e. investment levels in different corridors). The latter is particularly practical for problems with a low number of investment decision variables, since the problem remains more tractable in terms of cognitive capacity of a human brain (Miller, 1967).

Parallels could be drawn to the optimization literature from Figure 7. The figure summarizes all tradespaces for the considered epochs, including the "optimal solutions" (red dots) calculated by the TEP optimization program. That is, the optimization program treats the three transmission corridors in question as variables, in contrast to the tradespace generation/mapping (black dots) where grid capacity is given as parameters. The multi epoch nature of these comparisons are particularly relevant for the intuition behind uncertainty and stochastic programming. For instance, Figure 7 allows the reader to visually extract knowledge about the performance of designs that are calculated to perform well in a given scenario. The "optimal designs" for Epoch 1 and 2 (red dots labelled 1 and 2) does not perform particularly good in Epoch 3 and 4, which are scenarios with a quite different generation mix compared to Epoch 1 and 2 (see Table 4). Hence, there might exist more value-robust designs with respect to an uncertain future. Stochastic programming is a way to incorporate future uncertainty endogenously into an optimization program, yielding more robust solutions such as those within the fuzzy Pareto front (green dots in Figure 7).

An observation from the results is that the MATE provides valuable information not only for decision makers, but also analysts and model developers. For instance, general observations such as the tradespace structure yields an intuition about the nature of the problem – e.g. how more renewables (Epoch 4) affect the solution space and that this might require better decision-making tools. Moreover, mapping solutions from an optimization program into the tradespace yields visual insight and allows for multi-objective tradeoff (MATE) analysis. In addition, the use of tradespace could be invaluable for assessing utility functions since those might not uniformly exists for multinational systems such as the one presented here. That is, using the tradespace in a constructive way to ask decision makers and stakeholders about what they want and help them form priorities could serve an important part of the planning problem. Particularly in cases of multiple stakeholders where an aggregate utility function might be non-existing (Fitzgerald and Ross, 2016).

From the presented MATE framework, one of the main benefits is clearly the aspect of visually evaluating tradeoffs among multiple value attributes without relying on any heuristics (black box). That is, an "optimal solution" calculated by an optimization program can have multiple "neighbouring" solutions with considerable variations in value tradeoffs. For instance, one design yielding the maximum welfare ("optimal") might be surrounded by other solutions performing almost as good in terms of welfare but with more desirable performance in terms of e.g. CO_2 emissions or security of supply.

5. Conclusions

A generic methodological framework from the system engineering community is presented as an augmentation to the traditional transmission expansion planning (TEP), single-objective optimization approach. A majority of traditional TEP models are based on black-box optimization programs that yields one optimal solution, or a limited number of solutions, resulting in little or no insight for model developers, analysts, and consequently communication with decision makers. The Responsive System Comparison (RSC) method is used to structure the problem at hand and, in combination with a traditional TEP optimization model, generate insights by exploiting interactive plots for multi-attribute tradespace exploration (MATE) and multi-epoch analysis. The multi-epoch analysis is conducted using the concept of a k% fuzzy Pareto front and corresponding metrics such as the fuzzy normalized Pareto trace (fNPT), enabling decision makers to evaluate the performance of investment decision both for individual- and multiple epochs, where the latter allows for contextual uncertainty to be incorporated.

The value of combining tradespace exploration and optimization is demonstrated with a case study considering the expansion of three multinational transmission corridors in the North Sea Offshore Grid (NSOG). Decision variables are discretized in order to use the TEP model to simulate the tradespaces used for MATE and multi-epoch analysis. It is shown that this approach is suitable for problems with a relatively low number of decision variables, both in terms of tractability (number of simulations needed) and traceability (from performance to design). Results from the MATE and multi-epoch analysis is used to assess the added value for a practitioner in terms of more insights about the capacity planning problem in general, as well as for value tradeoffs across multiple value attributes such as welfare gains, CO_2 emission reductions, and security of supply. Finally, parallels are drawn to the optimization literature where the performance of optimal, deterministic solutions are visually shown over multiple epochs (scenarios), including the intuition of value-robust solutions that perform better over all considered scenarios which is also the case for optimal, stochastic solutions.

5.1.1. Shortcomings and future work

We present a multidisciplinary approach for the application of systems engineering methods on traditional TEP problems. Hence, there are naturally other less relevant aspects of the whole RSC method left out of the scope for this paper. For instance, the definition of value and utility is not based on stakeholder interviews nor is the TEP model a proper representation of reality – it is indeed an approximation. More importantly, we do also only consider one stakeholder from a European perspective. The view of a multi-stakeholder perspective is an interesting extension, using the MATE to visualize different stakeholders' contribution to system welfare – which could serve as a supplement to cooperative game theory studies questioning how much each stakeholder contribute and how costs and benefits could be distributed.

Regarding the discretization of decision variables, and thus the tractability in terms of reasonable simulation times, there is more work to be done in doing efficient discretization and parallelization of the TEP model simulations. For instance, one could use the TEP model to map important sample intervals that could decrease the number of necessary simulations.

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Appendix

Equations (1a)-(1l) lists the mathematical formulation of the optimization model used to generate design alternatives in this paper. The objective is to maximize system welfare, which is equivalent to minimizing investment costs (1b) and operational costs (1c), together yielding net present value of total costs (1a) by multiplying the annual operation costs with an annualization factor, a. The investment costs comprise of fixed- and variable costs, determined by the number of new transmission lines (y_b^{num}) and new capacity (y_b^{cap}), respectively, at branch, b. Moreover, z_n is a binary variable that determines whether to build an offshore platform/node for meshed infrastructure connections, meaning that you could connect e.g. two cross-border lines and one offshore wind farm to an offshore platform. Finally, all investment decisions are determined based on their performance in the electricity market dispatch (operational costs), i.e. marginal costs of generation g_{it} and load shedding s_{nt}, subject to the restrictions given in (1f)-(1l).

$$\min_{y,z,g,f,s} IC + a \cdot OC \tag{1a}$$

where

$$IC = \sum_{b \in B} \left(C_b^{fix} y_b^{num} + C_b^{var} y_b^{cap} \right) + \sum_{n \in N} C_n^{bus} z_n \tag{1b}$$

$$OC = \sum_{t \in T} \omega_t \big(\sum_{i \in G} (MC_i + CO2_i) g_{it} + \sum_{n \in N} VOLL \cdot s_{nt} \big) \tag{1c}$$

$$C_b^{fix} = B + B^d D_b + 2 \cdot CX \qquad \forall b \in B \tag{1d}$$

$$C_b^{var} = B^{dp} D_b + 2 \cdot CX^p \qquad \forall b \in B \tag{1e}$$

subject to

$$\sum_{i \in G_n} g_{it} + \sum_{b \in B_n^{in}} f_{bt}(1 - l_b) - \sum_{b \in B_n^{out}} f_{bt} + s_{nt} = \sum_{l \in L_n} D_{lt} \qquad \forall n, t \in N, T \tag{1f}$$

$$s_{nt} \leq \sum_{l \in L_n} D_{lt} \qquad \forall n, t \in N, T \tag{1g}$$

$$P_i^{min} \leq g_{it} \leq \gamma_{it} P_i^{max} \qquad \forall i, t \in G, T \tag{1h}$$

$$\sum_{t \in T} \omega_t g_{it} \leq E_i \qquad \forall i \in G \tag{1i}$$

$$-\left(P_b^e + y_b^{cap} \right) \leq f_{bt} \leq \left(P_b^e + y_b^{cap} \right) \qquad \forall b, t \in B, T \tag{1j}$$

$$y_b^{cap} \leq P_b^{n,max} y_b^{num} \qquad \forall b \in B \tag{1k}$$

$$\sum_{b \in B_n} y_b^{num} \leq M z_n \qquad \forall n \in N \tag{1l}$$

$$y_b^{cap}, g_{it}, f_{bt}, s_{nt} \geq 0, \quad y_b^{num} \in \mathbb{Z}^+, \quad z_n \in \{0,1\}$$

The nodal energy balance (1f), i.e. power flowing into node/area/country n has to equal the power flowing out, in addition to its own consumption. This is in line with Kirchhoff's current law. Moreover, the generators has to generate more power than its minimum limits (P_i^{min}) and less than its existing, maximum capacity (P_i^e) multiplied with an availability factor (γ_{it}) which is used to describe the hourly variations of non-dispatchable technologies such as solar and wind, as shown in Equation (1h). The power flow (f_{bt}) at a given branch b can flow in both directions and must therefore be greater- or less or equal to its maximum capacity ($P_b^e + y_b^{cap}$).

Table 6 - Notations for the transmission expansion planning (TEP) optimization program

Sets & Mappings		
$n \in N$	:	nodes
$i \in G$	:	generators
$b \in B$	:	branches
$l \in L$	:	loads
$t \in T$	:	time steps
$i \in G_n, l \in L_n$	:	generators at node n, loads at node n
$b \in B_n^{in}, B_n^{out}$	:	branches into node n, branches out of node n
$n(i), n(l) \in N$	:	generator i belongs to node n, load l belongs to node n
Parameters		
a	:	Annuity factor
ω_t	:	Weighting factor for hour t (number of hours in a time sample/cluster)
$VOLL$	:	Value of lost load
MC_i	:	Marginal cost of generation
$CO2_i$	:	CO_2 emission costs
D_{lt}	:	Demand at load l
B, B^d, B^{dp}	:	Branch mobilization, fixed- and variable costs
$C^{switch}, C^{switch,p}$	:	Onshore or offshore switchgear costs (fixed and variable)
C_n^{bus}	:	Onshore or offshore node installation costs (e.g. an offshore platform)
P_i^{max}	:	Maximum generation capacity
γ_{it}	:	Factor for available generator capacity (non-dispatchable inflow)
P_b^e	:	Existing branch capacity
$P_b^{n,max}$	:	Maximum new branch capacity
D_b	:	Distance/length, branch b
l_b	:	Transmission losses, branch b
E_i	:	Yearly disposable energy related to generator i
M	:	A sufficiently large number
Primal variables		
y_b^{num}	:	Number of new transmission lines, branch b
y_b^{cap}	:	new transmission capacity, branch b
z_n	:	New platform/station, node n
g_{it}	:	Power generation dispatch, generator I, hour t
f_{bt}	:	Power flow, branch b, hour t
s_{nt}	:	Load shedding, node n, hour t

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Paper J

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Paper J

Scenario Robustness and Cost-Benefit Allocation for Multinational Transmission Grid Investments

A North Sea 2030 Case Study

Martin Kristiansen and Magnus Korpås
Department of Electric Power Engineering
Norwegian University of Technology and Science
Trondheim, Norway
martin.kristiansen@ntnu.no

Philipp Härtel
Fraunhofer Institute for Wind Energy
and Energy System Technology
Kassel, Germany
philipp.haertel@iwes.fraunhofer.de

***Abstract*—This paper presents a case study quantifying the uncertainty in terms of deviation in transmission capacity investment decisions. The case study is conducted on the North Sea area, since this region has been identified as one of the strategic trans-European energy infrastructure priorities in the EU Regulation No 347/2013 as it potentially serves the twofold purpose of both integrating offshore wind power generation and cross-border trading. A mixed integer linear program (MILP) is used to cope with the nature of this transmission expansion planning problem (TEP), considering both multinational stakeholders and variable power generation from large-scale offshore wind power plants. ENTSO-E's four visions for 2030 are implemented as input data to evaluate the potential impact they have on the optimal offshore grid infrastructure. The behavior of Norwegian hydro power capacity is enhanced in the model to capture seasonal variations and a realistic duration curve. Results from this study gives different grid infrastructures for each scenario, varying in both rated capacity and new cables. The largest capacity deviations between the four scenarios were identified for the link between Norway and Great Britain. It is also shown that Great Britain and the Netherlands are exposed to significant investment needs in a meshed grid solution to integrate the offshore wind capacity. The paper further evaluates the effect of newly built capacity, its utilization, the need for onshore grid reinforcements, and finally the economic welfare from market operation. It is shown that the overall consumers benefit towards a "Green revolution" scenario in Vision 4.**

Keywords: Transmission Expansion Planning; Offshore Grid; Wind Integration; North Sea 2030; Cost-Benefit; Scenario Robustness.

I. Introduction

Due to ambitious decarbonization goals of the European energy system towards 2050 it is expected that, compared to the current level, renewable energy sources such as wind and solar will represent a larger share of the generation mix. The ongoing generation shift from dispatchable hydro-thermal generation towards fluctuating renewable feed-in in the respective generation portfolios is a main driver of energy system evolution as it demands increased flexibility of the energy system and yields a new allocation of power flows at the same time.

A. Need for Adequate Planning and Investment Models

Regarding potential wind resources, a significant amount of them is often located at geographical coordinates far from load centers and grid infrastructures, e.g. in the North Sea region. As a result of its wind potential and cross-border trading opportunities, the EU Commission has identified the North Sea area as one of the most strategic trans-European energy infrastructure priorities. In order to cope with the changing energy mix and strategic outlines made by policy makers, it is of great importance to evaluate proper planning models being suitable for multinational investments and increased uncertainty at the supply side in a future integrated market environment.

NetOp is a deterministic, mixed integer linear program developed by SINTEF Energy [1] for the purpose of analyzing offshore electricity grid infrastructures on a strategic level. The model incorporates static scenarios for a given year and consists of a top-level investor (TSOs) and a lower level market simulator. The lower level problem describes hourly market operation over a year, in which load profiles, wind power production, solar power production and water value time series [2] are sampled to account for some of the variability that the operating power system is exposed to.

The TEP model is used to evaluate scenario's robustness, in terms of how different scenarios might affect the investment decisions. An investment decision for larger HVDC interconnections might be executed many years before the actual project implementation and installation, hence it is of great importance to review the potential effects of using available scenarios outlined by long-term climate targets for the energy system. Given the planning horizon and implementation times, long-term scenarios must be employed to incorporate development pathways of the energy system in grid investment analyses. The presented study thus uses four different long-term scenarios from the annually published Scenario Outlook & Adequacy Forecast (SO&AF) as a data set for a 2030 case study of the North Sea.

The work has been carried out at NTNU, in close cooperation with SINTEF Energy and Fraunhofer IWES under the project North Sea Offshore Network (NSON).

The model output from each scenario is used to quantify the significance of the uncertainty implied by the European TSOs. Both direct investment decisions, as well as impacts on the power system welfare due to market operation, will be used to study the range of possible outcomes. This will form a fundament for further investigations of improvement potentials related to the development of TEP models. Of particular relevance is the value of handling uncertainty, distributional effects, and disruptive system properties such as intermittent power production and storage or other flexibility options like capacity markets.

B. Previous work on offshore grids

Offshore grid development has been the subject in a number of previous as well as ongoing studies and research projects on a national and international level. These have investigated various offshore grid design options with different sets of scenario and parameters, often with a special focus on the North Sea area. Among them, several studies have already been assessing the benefits accompanying the potential deployment of offshore grids on an overall region level, prominent studies include [1], [3], [4] and more recently [5]. As one recurring conclusion, meshed offshore grid structures as opposed to radial grid designs were generally found to offer benefits for the overall region.

Beyond looking at the aggregated cost-benefit allocation on an overall system level, few studies have analyzed offshore grid benefits for the individual market areas. Focusing on welfare implications of different scenarios and grid designs, [6] analyze three different offshore grid developments, ranging from a rather nationally focused development to a full European integration. They conclude that a clear distinction has to be made between the overall benefits of an offshore grid in the North Sea area and the individual national gains. Further, their results indicate that the impact of offshore grids on consumer and producer rents is significantly higher than the shifts in aggregated national welfare within the power system.

The North Sea Transnational Grid (NTSG) project [7] investigated costs and benefits of a future offshore grid built in the North Sea. It studied the effects of a radial connection of offshore wind farms as well as a connection by means of a future offshore ring linking the six offshore grid countries, the United Kingdom, Norway, Denmark, Germany, the Netherlands and Belgium. In line with the findings mentioned above, they conclude that the net benefits for the

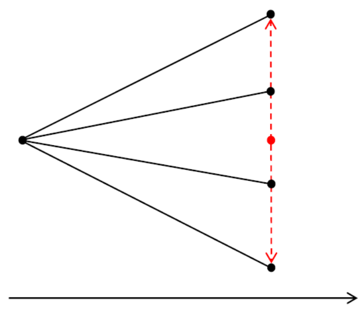

Figure 1. The red dotted line illustrates optimal grid infrastructures for different market states. The black dots represents ENTSO-E's four visions as possible market states.

whole of Europe are higher in the Full Ring scenarios, although their results indicate that they are not beneficial for the six direct offshore grid countries being responsible for building the offshore grid.

More recently, [8] performed cost, benefits and risk studies for three pre-defined cases of potential offshore transmission infrastructure projects (German Bight, Benelux-UK and UK-Norway) comparing integrated and isolated design approaches. The assessments also include intra-country distributive impacts on net socio-economic welfare with a range of cross-border cost allocation methods.

In summary, previous studies have shown the importance of including the cost-benefit allocation not only on a country level, but also on a stakeholder level into the assessment of investment decisions concerning multinational offshore transmission infrastructure.

One of the relevant contributions of this paper is that we have included a spot price time series to reflect seasonal variations in the hydro-dominated power market in Norway. Moreover, onshore AC grid capacities are treated as variables in the optimization problem, giving an indication as to how important enhancing the mainland infrastructure nearby the offshore grid connection-points is. Finally, ENTSO-E's four visions are implemented in the TEP model with the purpose of "translating" possible market situations (in 2030) into respective grid infrastructures optimized by NetOp. There is reason to believe that this can provide a good basis for future studies regarding stochastic programming, as well as more dynamic investment models.

II. METHODOLOGY

The idea of this research is to illustrate the effect of a scenario set for power generation and demand on TEP. A transmission system operator is exposed to investment risks involving sunk costs for assets with a very long lifetime. Hence, it is crucial to make robust decisions in this context. In this paper, we will study four possible market developments forecasted by ENTSO-E with the goal of evaluating their implications by optimizing a grid infrastructure for each market state. An illustration of the methodology is shown in Fig. 1 where the red-dotted line spans the opportunity space for an optimal grid. In order to quantify the deviations in investment decisions for a set of distinctive scenarios, we need an investment model. A deterministic and static MILP TEP model is employed to optimize the need for additional power transmission capacity between market areas and offshore power plants. Reflecting a bridge between the 2020 and 2050 energy targets in the EU, a set of scenarios from ENTSO-E is used in this study [9]. A more detailed discussion of its four evolution scenarios considered here are given in Section III.

Section II starts with an introduction of the investment model NetOp, including a discussion of its limitations while simultaneously pinpointing potential improvements for a future model development. One underlying objective of this paper is to stress the need for novel TEP models better managing uncertainty. For a more detailed presentation of the model and its mathematical formulation, it is recommended to consult [1].

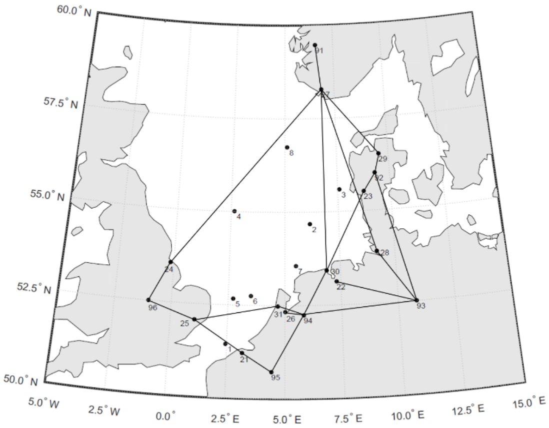

Figure 2. NetOp model - The North Sea area with onshore- and offshore nodes (black dots), existing- and commissioned branches (black lines) by the year 2030

A. *Investment Model (NetOp)*

NetOp is a mixed integer linear program modelled as a top-level strategic investor, making investment decisions for all countries bordering the North Sea area. Fig. 2 shows a plot of the nodes that are included in the model, as well as already existing and commissioned branches representing a base case for 2030. The objective function in the optimization problem is to minimize total system costs, given the assumption of perfect competition in the power market. This means that electric power is always produced from the generator with the lowest marginal cost, and there are no strategic players participating in the market.

One of the key strengths of the model is that it accounts for the variability of load, solar and wind power generation, and more recently also water values. This is achieved by sampling from yearly profiles with an hourly resolution. Out of theoretically 8760 possible samples, analyses in this paper are based on 200 samples. The choice of the sampling number is based on findings in [1] showing that 200 samples give robust results in terms of stable generation and investment costs. All time series that NetOp samples from are correlated with each other and given by previous work in the TradeWind project [10], adjusted for peak demand and installed generation capacity from the scenario data sets used in this paper [9]. It should be noted that time series for intermittent power production, such as wind and solar, are based on simulations of spatial and temporal meteorological weather data over 10 years using reanalysis [11].

The choice of technology, e.g. whether to choose AC lines or HVDC cables in combination with AC/DC converters. Compared with AC grid options, required technology for a meshed HVDC infrastructure solution is considered capital-intensive to reflected the current feasibility level. For branch distances over 100 km, HVDC connections are automatically chosen as the preferred technology.

Power losses are included as constant fractions of the power flow through a given component. This is considered as a good approximation since there is a limited amount of loop flow situations due to few AC lines and mostly controllable HVDC interconnectors, subject to net transfer capacities (NTCs). Hence, loop flow effects are assumed to only have a minor impact on the overall optimal solution. The network depicted in Fig. 2 uses the same zone configuration for synchronous areas as the TradeWind project. Updated NTC values and newly commissioned transmission capacities are also included to reflect a realistic base case scenario for 2030 [9], [14].

The North Sea area borders to six countries in the model, namely Norway (NO), Denmark (DK), Germany (DE), the Netherlands (NL), Belgium (BE), and Great Britain (GB). These countries represent a major part of the annual turnover in the European power markets. However, the fact that the data set does not include surrounding countries can be viewed as one weakness when considering the level of detail on market prices and cost-benefit allocations, especially in terms of the inability to evaluate free-rider effects. The latter term refers to indirect impacts on market areas also being connected to the countries listed above, but which are not contributing to the cost recovery of the investments.

Another important assumption regarding the AC infrastructure in the model is that each country has one load center, meaning that distributional effects related to interconnecting nodes are neglected. Anyway, in this paper we include the connections to the load centers as variables in the optimization problem, wherefore additional capacity is added if optimal. This gives an indication as to how strong there is a need for extending the onshore AC grid.

The locations of offshore wind power plants are based on the ones that are placed farthest from shore, e.g. such as node 8 and 4 in Fig. 2. This means that country-specific offshore wind capacity, given by the scenario sets, is aggregated at these locations. Hence, the model lacks the ability to simulate the geographical smoothing effects due to wind speed variations and realistic power flow through the electricity infrastructure. It should therefore be kept in mind that the model can overinvest in branch capacity, if too much wind power capacity is allocated to only one node. In NL and GB, two offshore wind power nodes are included to cope with this problem to some extent.

B. *Socio Economic Measures*

As stated in Section I, previous studies have considered the importance of cost-benefit measurements and allocation. Quantifying socio economic welfare in the power system is one way of coping with this issue. A graphical illustration of the calculation procedure can be found in [6], and a thorough description of the methodology can also be consulted in [14]. The next paragraph will however summarize the basics of calculating the producer and consumer surplus, due to power market operations.

For obtaining the producer surplus, the total quantity sold in the market is multiplied by the clearing price and subtracted by the generation costs. In a graphical context, this is the same as the integral below the market price and above the supply curve. A similar procedure can be used for determining the consumer surplus. Its potential gain, in contrast to the supply side with the marginal cost, is the difference between the consumers' willingness to pay for electricity and the market price, i.e. the area under the demand curve and above the clearing price. In this paper, the price for energy not served is set to 375 EUR/MWh for each price area, which is based on Norwegian conditions, see [2].

Net export from a node is also considered, whether it is larger than zero or less than zero. The demand curve or the supply curve for the node price is shifted accordingly. Losses are neglected in the calculation of economic surplus, since the paper only studies relative results.

III. Case Study

The Case Study section gives a detailed introduction to the ENTSO-E visions used in this paper.

A. 2030 Visions of ENTSO-E as a Scenario Reference

As indicated earlier, the following case study of the North Sea region is based on the 2030 Visions of ENTSO-E. These scenarios are also being used in the Ten-Year Network Development Plan (TYNDP) outlined by EC 714/2009 [9]. The four 'Visions' specified therein represent a bridge between the EU targets for 2020 and 2050, under different assumptions for the future evolution of key parameters mapping the range of uncertainty. Reflecting similar boundary conditions and economic developments for every country, these contrasting scenarios differ enough from each other to cover a realistic range of possible future pathways and challenges for the grid infrastructure [14]. As part of the scenario based approach, the four Visions limit the number of scenarios for the analysis of the adequacy of the future grid. Two axes are employed to formulate the four evolution scenarios mapped at the corners of their outer edges, as illustrated in Fig. 3.

One axis represents the development of renewable energy sources and compliance with the EU Energy Roadmap 2050 aiming at greenhouse gas emission reductions to 80-95% below 1990 levels [13]. Its upper end implies the energy system being on track with the EU Energy Roadmap towards 2050 while at the lower end severe deviations from targets and delays are expected. The second axis depicts the progress towards a strong or loose European framework facilitating its decarbonization process. Therefore, on this axis a high degree of European integration with a unified approach of setting and achieving goals opposes a low degree of integration without a common vision of Europe's future energy system and rather separate national approaches.

Fig. 4 shows existing and expected wind generation capacities for 2030 in the North Sea region. Regardless of the four Visions, expected offshore wind capacities in this area lie within a range of 38-110 GW and are therefore substantially higher than existing capacities. By comparing Vision 1 and 2 against 3 and 4 it becomes clear that both the

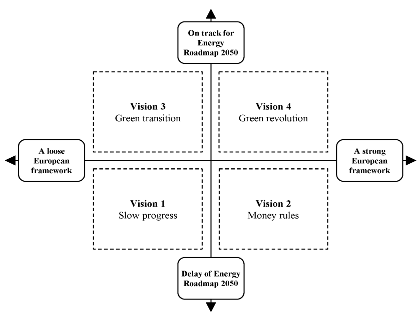

Figure 3. Two axes and the four 2030 Visions of ENTSO-E for assessing challenges and opportunities of the future European grid infrastructure, based on [5].

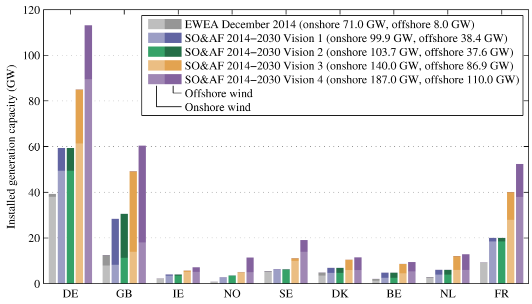

Figure 4. On- and offshore wind generation capacities in the North Sea area, current installations [14] and expected future scenarios in 2030 [9].

"Green transition" and "Green revolution" scenario are based on significantly higher wind on- and offshore generation capacities than the "Slow progress" and "Money rules" scenarios. The major share of wind offshore generation capacity can be attributed to Germany and Great Britain.

IV. Results

Market integration and more cross border grid infrastructure give increased trade opportunities between the countries. In total, one can argue for a more efficient market – actually almost perfect considering that there are no restrictions on grid investments. This section confirms that by moving towards the "Green revolution" scenario, the system demands more flexibility in terms of a stronger grid with cross-border trading of electricity. The investment costs in each vision vary between 10.5 bn€ and 32.3 bn€, and the overall system costs deviates the most from Vision 2 to Vision 4 with an equivalent annual cost of 6.9 bn€/year.

The results are introduced by reviewing the investment decisions made in each vision, illustrating the uncertainty of which grid layout is the most optimal. Finally, a discussion regarding the cost-benefit measurements are presented at the end of this section.

A. Investment Decisions

None of the scenarios gives exactly the same optimal infrastructure or branch capacity. The variation in optimal grid capacity is clearly illustrated in Fig 5 in which Vision 1 is depicted in the top-left corner and Vision 4 in the bottom-right corner. The thicker the line plot is, the larger the new installed transmission capacity. The indication level is set to larger than 5 GW, 3 GW or 1 GW.

1) Direct Connections: There is no clear consistency among the results, but one can see that the NO-GB interconnector varies the most, followed by NO-DK. According to Vision 2, GB does have more installed capacity of nuclear, coal and onshore wind than in Vision 1, which suggests a smaller dependency on additional interconnectors to and from the mainland. In Vision 3 however, GB has considerable less natural gas generation capacity than in the first two visions, in addition to almost twice as much offshore wind capacity. This demands more flexibility through interconnectors, especially to Norwegian hydro power capacity, hence the large capacity investments

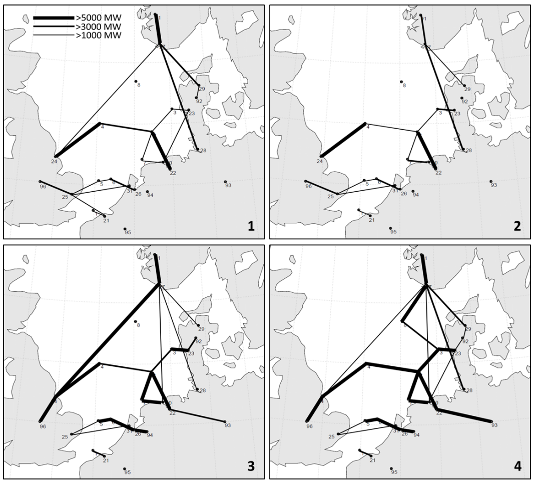

Figure 5. Infrastructure capacity investments for Vision 1 (top left) to Vision 4 (bottom right). The thickness of the line plots indicate the size of new investments beyond the base case scenario for 2030, ranging from large (>5 GW), medium (>3 GW), and small (>1 GW).

on the NO-GB interconnector. In NO, there are no major changes in either the supply- or demand side, moving from Vision 1 to Vision 3.

Other direct connections are mainly driven by the installed capacity of offshore wind power. The connection of the offshore wind power plants in BE is one example. Since we use zero marginal cost for wind in the model, the grid investment becomes profitable at a relatively low level of installed wind power capacity. Curtailment costs, due to insufficient transmission capacity, might even increase the investment signal for additional capacity. For the Norwegian offshore wind power plant, the investment costs for the branch relative to the installed capacity of offshore wind power amounts to 0.3 M€/MW.

2) Meshed Offshore Grid: A meshed structure is chosen for the offshore wind power plants in Vision 4. According to the size of the cables attached to this node, a net import from the offshore wind power plant seems to be expected. The offshore joint allow for cross border trade with DK, DE, NL, and GB – which serves as an explanation for the decrease in new capacity at the radial interconnectors.

The most robust investments are the domestic cables out to offshore wind power plants in GB (node #4) and in the NL (node #2), each of them correlating with the size of the wind power capacity in Fig. 4. A strong meshed grid infrastructure is established around the offshore node (#2) in the NL, and one can see the pattern from low-level offshore wind power capacity in Vision 1, to high-level capacity in Vision 4. The demand for flexibility is being allocated out to multiple load centers, and flexible generation sources.

3) Onshore AC Infrastructure: In each vision the system demands flexible hydro power generation from Norway, requiring onshore grid reinforcements in the range of 1000 MW to 8000 MW of additional capacity compared with the 2030 base case. In GB it can be seen that the need for onshore grid reinforcements is shifted from a south-east to a north-east layout when moving towards "on-track" European energy targets. This might be due to the fact that a large share of the offshore wind power capacity is allocated to the Doggerbank node (#4), in combination with the flexibility provided by the meshed grid infrastructure available around it.

The offshore meshed grid implies to be the driver for most of the onshore grid reinforcements, centralizing the cross-border power flow over shorter distances offshore, rather than longer interconnectors onshore. The results show that this is also the case for DE in the high renewable energy source (RES) scenarios.

B. Cost-benefit Allocation

The zonal prices calculated in this analysis suggest that NO has the lowest price on average for all visions. The other countries operate more or less at the same price level, since generation from natural gas, bio and coal serves as the marginal producer. However, the prices in DK decrease towards the same level as in NO in Vision 4, which is mainly due to the combination of high wind penetration and larger exchange capacity with NO.

1) Consumer Surplus: The consumer surplus is increasing in all countries from Vision 1 to Vision 4 as seen in Fig. 6, both country-wise and from a system perspective. The most interesting observation is that it increases for NO as well, which already has a relatively low market price. The zonal price for this country experience a minor increase from Vision 1 to 2, so the accumulated consumer surplus has to be a result of increased trade – which in this case primarily is with DE due to an increased demand, but a relatively stable supply side.

The consumers benefiting the most are those who have relatively high market prices, particularly GB and to some extent DE. Moving from a low-level RES market towards a strongly integrated market with high shares of RES, these countries will experience a decrease in market prices which will benefit the consumers.

2) Producer Surplus: Even though market prices drop and some generation sources with high marginal cost are utilized less than before, one can still observe a slight increase in producer surplus in Fig. 6. However, from a system perspective the producers' surplus is highest in Vision 2, and decreases towards Vision 4 resulting from GB's and DE's strong influence.

Another interesting observation is the difference in producer surplus between Vision 1 and 2 for GB. GB originally has a large share of natural gas capacity in its generation mix, and the most reasonable explanation for this result is that natural gas based production is a dominating marginal producer in Vision 1. Considerable amounts of generation capacity with lower marginal costs are being introduced to the mix in Vision 2, causing a

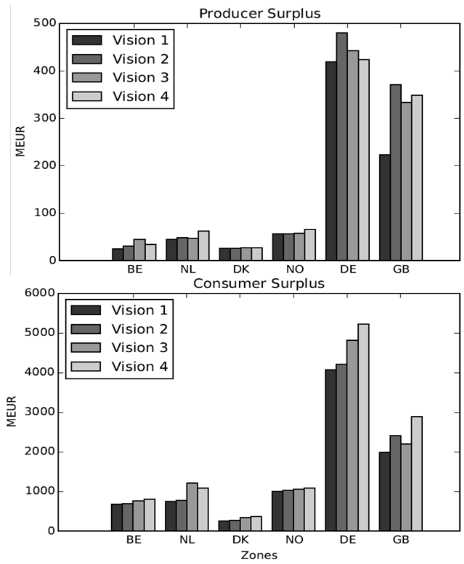

Figure 6. Producer- and consumer surplus calculated for each country as a result of the optimal grid investments in NetOp based on ENTSO-E's four visions.

positive shift in the supply curve. According to the zonal price for GB, the marginal producers are still natural gas plants but at a lower market share than in Vision 4, leaving the producers in total with lower generation costs and more surplus.

V. CONCLUSION

A mixed integer linear program has been used to study a set of scenarios for the power system in North Sea area during 2030, with the purpose of evaluating the scenarios impact on transmission expansion planning. The results show that the room of uncertainty represented by ENTSO-E's four visions for the generation mix and demand in 2030 can have a significant impact on the investment signals for an optimal grid infrastructure. The investment costs in the visions vary between 10.5 bn€ and 32.3 bn€, where the largest deviations at individual transmission lines are found in relation to partly isolated price areas like Great Britain. The total system costs decrease at most, from Vision 2 to Vision 4, by an equivalent annual cost of 6.9 bn€/year, as more renewables are being introduced to the generation mix, and price areas are integrated through new transmission capacity.

Cost-benefits, in terms of socio economic measures, have been quantified for each country in all scenarios. On the overall system level it can be shown that the producers might experience a smaller (market) surplus moving towards Vision 4, i.e. a "Green revolution", while the opposite is the case for the consumers. Both Germany and Great Britain are exposed to a considerable increase in producer surplus from the "Slow progress" to "Money rules" scenario, of which the latter one is the most favorable scenario of them all. Overall, the consumers do benefit the most in the "Green revolution" scenario. Using an inelastic demand in the optimization, the shape of the merit order supply curve is the key driver for those figures. Increased trade through intraday markets might even result in higher system surplus than could be evaluated in the context of this study, as it only considers the day-ahead market.

Altogether, it is shown that distinctive, yet realistic, scenarios can have considerable impacts on both infrastructure investments and socio economic indicators due to power system economics. Even if one grid infrastructure is optimal for one scenario, this does not necessarily mean that it is not profitable for another outfall/scenario – this is left for future studies to evaluate. In conclusion, this study underpins some important factors regarding TEP modelling and for the main part stresses the potential value of accounting for uncertainty.

ACKNOWLEDGMENT

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```python
@author: Martin Kristiansen
"""
# Import neccessary tools and packages
import powermodel
import powermodel.powergim as pgim
import pyomo.environ as pyo
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

path_in = "data_input/"
path_out = "results/"

# ============================================================================
#  Read input data
# ============================================================================
print("Collecting grid input data")
grid_data = powermodel.GridData()
grid_data.readSipData(nodes = path_in+"nodes.csv",
                      branches = path_in+"branches.csv",
                      generators = path_in+"generators.csv",
                      consumers = path_in+"consumers.csv")
grid_data.readProfileData(filename = path_in+"profiles/profiles.csv",
                          timerange = range(8760),
                          timedelta = 1.0)

# ============================================================================
#  Reduce the size of the time series (this is called "sampling" or "clustering")
# ============================================================================
print("Sample new time steps...")
samplesize = 200
pd.np.random.seed(2017)
timerange = pd.np.random.choice(8760, size=samplesize, replace=False)
grid_data.readProfileData(filename=path_in+"profiles/profiles.csv",
                          timerange = timerange,
                          timedelta = 1.0)

# ============================================================================
#  Formulate the optimization model
# ============================================================================
print("Formulating model...")
sip = pgim.SipModel()

# Convert the data input to an input format that the model understands
dict_data = sip.createModelData(grid_data,
                                datafile=path_in+"parameters.xml",
                                maxNewBranchNum=10,
                                maxNewBranchCap=10000)

# Formulate the final model with parameters
cmodel = sip.createConcreteModel(dict_data)
#cmodel.pprint('results/my_model.txt')

# ============================================================================
#  Solve the resulting optimization problem with a "solver". Use "cplex" or "gurobi"
# ============================================================================
print("Solving optimization model...")
opt = pyo.SolverFactory('gurobi')

results = opt.solve(cmodel, tee=True, #stream the solver output
                    keepfiles=True, #print the LP file for examination
                    symbolic_solver_labels=True) # use human readable names

print("Finished!")
# ============================================================================
#  FINISHED! The optimization problem is solved. Now; collect and present the results, for example like this:
# ============================================================================
sip.saveDeterministicResults(model=cmodel, excel_file=path_out+'Results_byPowerGIMscript.xlsx')
```

Figure 1: This script demonstrates how easy it is to run PowerGIM. First read relevant input data, then perform sampling/clustering if necessary, run the model, and use built-in functions to visualize or save results. The model library can be downloaded here https://bitbucket.org/harald_g_svendsen/powergama/wiki/Home.