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

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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.
Keywords: Energy Policy, North Sea Offshore Grid, Power System Flexibility, Renewable Integration, Shapley Value, Transmission Expansion Planning

1. Introduction

The European power system is exposed to large-scale integration of renewables the coming decades (European Commission, 2011), demanding more flexibility in order to distribute, consume, or store variable levels of power feed-in (Auer and Haas, 2016). 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 (Lund et al., 2015). 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 (Cochran et al., 2014). More electricity grid is needed in order to reach future energy- and climate targets and ENTSO-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 (ENTSO-E, 2016). One of the main challenges when it comes to planning for such investments is the geographical span that needs to be considered (Lumbreras and Ramos, 2016). 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 (Huertas-Hernando et al., 2017).

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 (Hogan, 2011). 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 (Sauma and Oren, 2007) focusing on distributional effects of transmission expansion. In Egerer et al. (2013) 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 (Perez et al., 2016).

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 (Konstantelos and Strbac, 2015). 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 (Ferguson, 2014) in order to cope with the aforementioned context. More precisely, we exploit the properties of The Shapley Value (SV) (Lloyd S. Shapley, 1953) 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 exibility 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 reviewes by Lumbreras and Ramos (2016) and, with a focus on multinational offshore grids like the NSOG by Gorenstein Dedecca and Hakvoort (2016). It has been shown that there is an underlying value in capturing system dynamics over larger areas due to smoothing effects (Hasche, 2010). 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 (Hogan, 2011), meaning that cost-efficient equilibria are not met if not considering both transmission and generation expansion due to its synergies on cost recovery (Munoz et al., 2012). Other challenges in the GTEP literature include, but is not limited to, incorporation of uncertainty (Munoz et al., 2014), representation of loop flows (O'Neill et al., 2011), distributed generation, demand side management, detailed energy storage handling, and FACTS devices (Hemmati et al., 2013). 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 (2016) 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 (Electric Power Research Institute, 2014). 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 (Cochran et al., 2014). 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 (Lund et al., 2015).

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. (2013). Moreover, Huber et al. (2014) 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. (2015) 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 (2015) 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 (Kondziella and Bruckner, 2016). 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 (1992) analyzing fair transmission pricing policies, followed by the first applications on transmission expansion planning by Contreras and Wu (1999) calculating fair cost allocations. Both papers applies The Shapley Value (Lloyd S. Shapley, 1953) 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 (Faria et al., 2009) and benefit-based expansion cost allocation in context of renewable integration (Hasan et al., 2014). 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 multinational 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 (Dabbagh and Sheikh-El-Eslami, 2015), remuneration to participants in demand response programs (O'Brien et al., 2015), or for calculating fair allocations of costs and benefits among microgrid agents (Lo Prete and Hobbs, 2016). Still, no applications considering flexibility technologies.

Banez-Chicharro et al. (2017b,a) 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 (Junqueira et al., 2007). 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 (Kondziella and Bruckner, 2016).

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 (Trötscher and Korpås, 2011) and more recently (Kristiansen et al., 2017b), which is available online in the same git repository as the pan-European market simulator; PowerGAMA (Svendsen and Spro, 2016). A list of notations for the GTEP model presented in following subsections can be found in Appendix A.

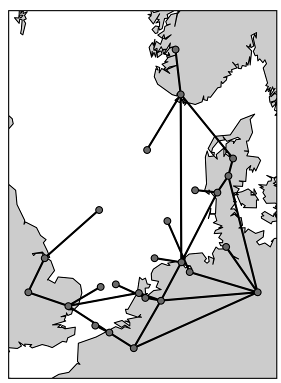

Figure 1: Base case for North Sea grid infrastructure (year 2016). Demand and generation capacities are given for year 2030 (ENTSO-E, 2014).

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 Figure 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) (Samuelson, 1952). 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

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

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

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

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

subject to

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

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

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

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

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

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

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

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. 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 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 (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). 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 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., 2017a). 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 (ENTSO-E, 2014), 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 0-100%. Moreover, RES-thermal capacity operates with a marginal cost (37.30 e/MWh on average) and CO2 emission rate (0.31 tonCO_2/MWh_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 exibility 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 avialability 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 e/MWh (Ian Hoffman et al., 2015). 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 e/MWh (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.

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[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 (Moura and de Almeida, 2010). 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 (ENTSO-E, 2014), in addition to an assessment of Norway as a green battery in 2030 (Gr v et al., 2011), studying the potential for hydropower expansion.

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 (Littlechild and Owen, 1973) where the SV is used to calculate a fair airfield maintenance fee to airplanes of different sizes, i, since each airplane has different impact on airfield requirements and maintenance cost. Another example is The Bankruptcy Game (O'Neill, 1982) 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 Equation (2).

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

The characteristic functions $v(\cdot)$ in Equation (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 bene ts of exibility 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 0-100%. 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 ($S \quad N$) 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 (ENTSO-E, 2014), yielding inefficient grid capacity. However, we allow for load shedding at VOLL e/MWh.

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 (ENTSO-E, 2014).

4.2. Geographical spread of exibility needs

Figure 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

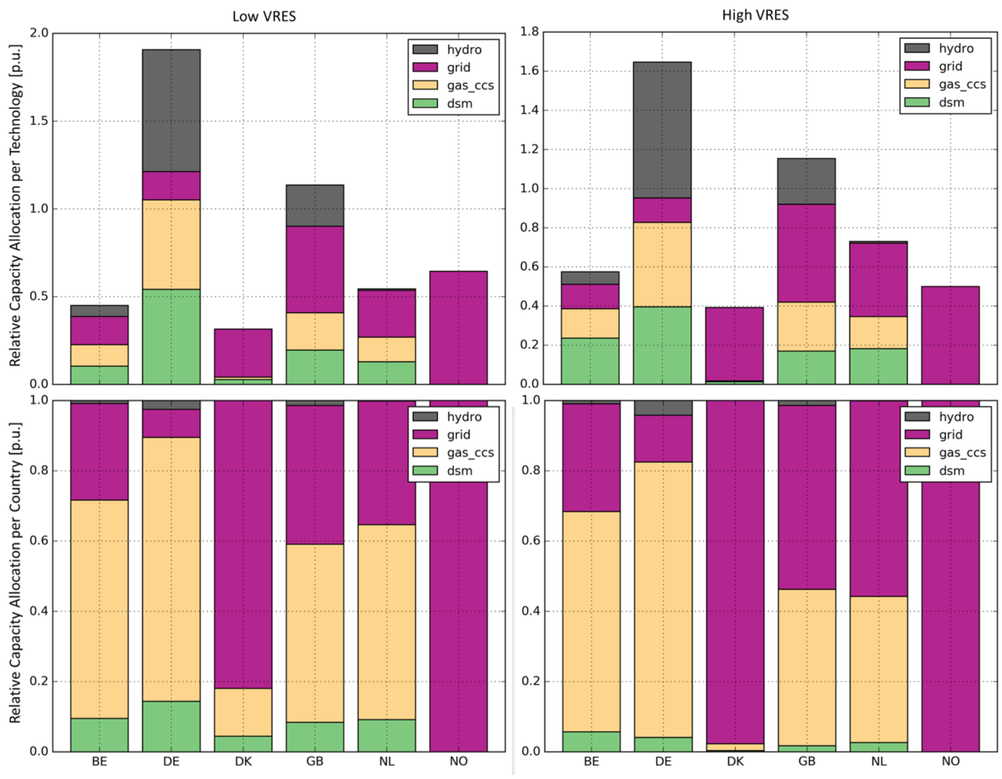

Figure 2: Relative capacity by technology (upper plots) and by country (lower plots) under low share (left part) and high share (right part) of renewables. Relative values sums to one. Input data from ENTSO-E Vision 4 (ENTSO-E, 2014).

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 Figure 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 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, Figure 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. (2015).

4.3. Marginal value of each exibility provider

Individual flexibility providers are assessed in a system context by quantifying its marginal impact on operational costs, as shown in Figure 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

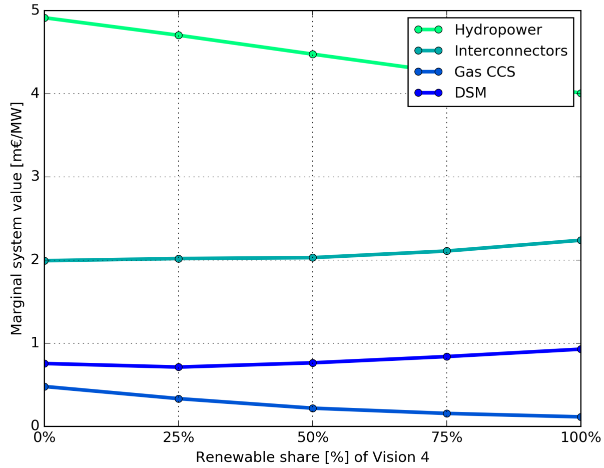

Figure 3: The marginal value per unit capacity (me/MW) for each exibility provider in terms of operational cost savings at system level.

stays about constant at m0.9e/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 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 hours with very high wind- and solar feed-in, in combination with low demand).

4.4. Aggregate contribution to system bene ts

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 Figure 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 Figure 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

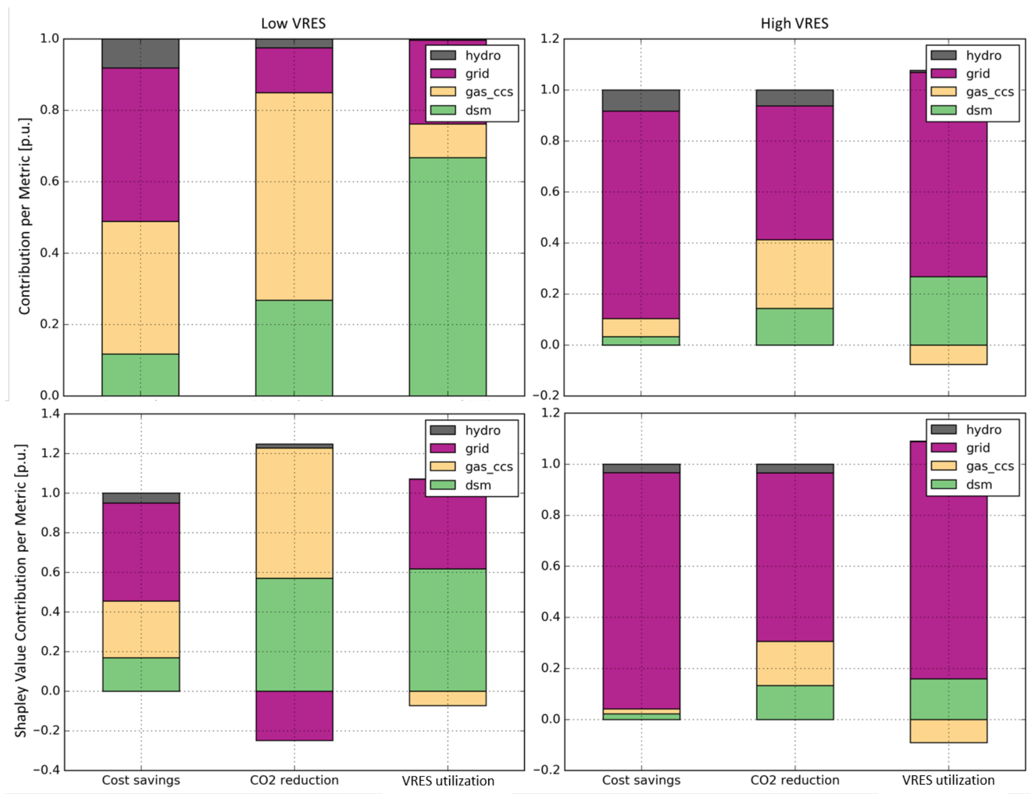

Figure 4: Relative bene t contribution to the system in terms of cost savings, reduced CO_2 emissions, and increased utilization of renewable supply (reduced curtailment). The upper two plots shows the implicit value added by each technology option (traditional aporach), while the lower two plots shows the value added for a range of possible deployment sequences (Shapley Value). Both for low- (left) and high (right) levels of VRES.

Table 1: The di erence between the traditional approach and the Shapley Value in Figure 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 exibility 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%

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 Figure 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.

Again, from Figure 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 0-100% 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 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 (Svendsen and Spro, 2016), which can be downloaded at bitbucket.org. The authors would like to thank the developers behind PYOMO (Hart et al., 2012), in addition to Gurobi Optimization and anonymous referees for constructive feedback.

Appendix A. Notations for GTEP model (PowerGIM)

Table A.2: Notations for the generation and transmission expansion planning model.

Sets	
$n\ 2\ N$	: nodes
$i\ 2\ G$	: generators
$b\ 2\ B$	: branches
$l\ 2\ L$	: loads, demand, consumers
$t\ 2\ T$	: time steps, hour
$i\ 2\ G_n, l\ 2\ L_n$	: generators/load at node n
$n\ 2\ B_n^{in}, B_n^{out}$	: 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) [e/MWh]
MC_i	: marginal cost of generation, generator i [e/MWh]
$CO2_i$	: CO_2 emission costs, generator i [e/MWh]
D_{lt}	: demand at load l, hour t [MW]
C_b^{fix}, C_b^{var}	: fixed- and variable capital costs, branch b [e, e/MW]
B, B^d, B^{dp}	: branch mobilization, fixed- and variable cost [e,e/km,e/kmMW]
CS_b, CS_b^p	: onshore/offshore switchgear (fixed and variable cost), branch b [e,e/MW]
CX_i	: capital cost for generator capacity, generator i [e/MW]
CZ_n	: onshore/offshore node costs (e.g. platform costs), node n [e]
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 [MWh]
M	: a sufficiently large number
Primal variables	
IC, OC	: investment- and operational costs [e]
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]

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