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Multistage grid investments incorporating uncertainty in offshore wind development

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Abstract

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 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.

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Keywords:
Transmission Expansion Planning, North Sea, Offshore Wind, Uncertainty, Flexibility

Nomenclature

EVPI	Expected value of perfect information	c^T, q^T	Cost vectors
NSOG	North Sea Offshore Grid	$x, y(\omega)$	First- and second stage variables
MILP	Mixed-integer linear program	$A, W, T(\omega)$	Model instance matrices
ROV	Real option value	$b, h(\omega)$	Resource-/limitation vectors
TEP	Transmission expansion planning	$\omega \in \Omega$	Discrete scenarios
VSS	Value of a stochastic solution		

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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 synergistic effects in variable renewable energy source 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 recover 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 transmission expansion and trading has been an important research topic due to its considerable impact on national welfare [8], in addition to recurring effects in 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 regarding 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 advancements in operations research, making it possible to include more details in the models [10]. In a recent literature review [11] they assess TEP studies related to the NSOG and find, among other things, a lack of research that incorporates uncertainty. The most qualified findings within 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.

TEP models that incorporate uncertainty include [13] and [2], which also has been studied in combination with generation expansion planning (GEP) by [14] and [5]. The latter two papers calculates the value of accounting for uncertainty compared with more traditional approaches. Moreover, as the model complexity rapidly increase when increasing the number of scenarios, i.e. accounting for uncertainty, the computational aspects become crucial and [15] reviews decomposition techniques for stochastic programs in this regard. One occurring program setup, except the ones presented in [14] and [2], is the assumption of an investor making one investment decision at the beginning of the analysis period, and disregards the opportunity to postpone, meaning that the real option value is ignored since it can be beneficial to learn more about uncertain data before a decision is made.

In this paper 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 only uncertain parameters in our study. The results illustrate topological effects for the NSOG in year 2030 and 2035, in contrast to [14] and [2] that focus more on numerical results

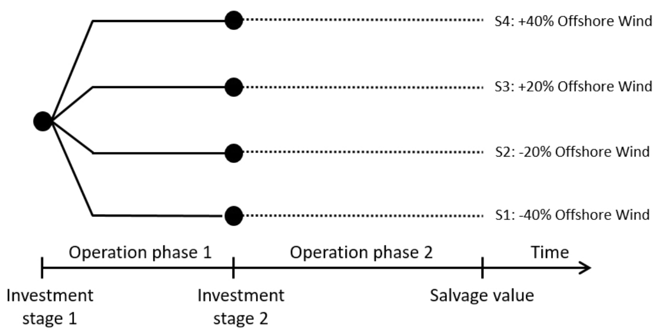

Fig. 1. Illustration of the timeline and uncertainty in offshore wind capacity deployment. Investments in grid capacity are made before (stage 1) and after (stage 2) the final wind capacity is revealed, calculated as +/- 40% of base case (ENTSO-E Vision 4 year 2030).

for a case study of Great Britain and IEEE-RTS, respectively. Hence, to our knowledge, the main contributions from this paper comprise of 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 paper 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 provides 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.

2. Methodology

To carry out the evaluation of infrastructure investments under uncertainty, we present a 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. Note that we assume zero construction time for all investments and we do not allow for generator capacity expansion in order to narrow the scope of this paper.

As a benchmark to evaluate the expected value of this approach, a deterministic equivalent is solved for one scenario at a time with 100% probability, yielding 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.

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

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

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

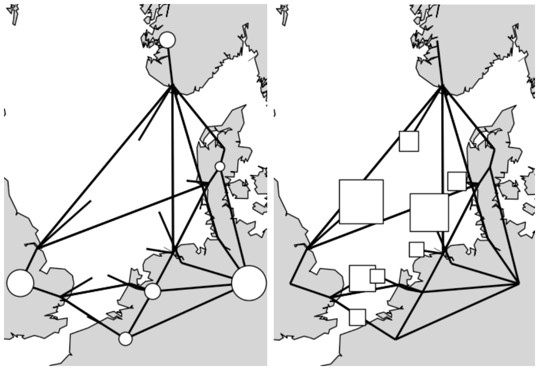

Fig. 2. Base case - NSOG for year 2030 including both existing and planned interconnections. Offshore wind connections are also included with higher transfer capacity than the installed offshore wind capacity, in order to narrow the scope to a pure interconnection analysis. Relative peak load (left plot; circles) and relative offshore wind capacity (right plot; squares).

The 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. 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 takes into consideration when making the first investment decisions in stage one (ENTSO-E Vision 4) [18]. 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 Figure 1, meaning that the cost vectors has to be discounted accordingly (5%) to their net present values in addition to calculating any salvage value for assets with remaining economic lifetime (after 30 years).

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 are independent on the realization of ω.

2.2. Preprocessed input data

We use time series data from the numerical weather prediction tool COSMO EU [19], 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. offshore wind speeds.

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, for instance [16], argues that 200 time steps

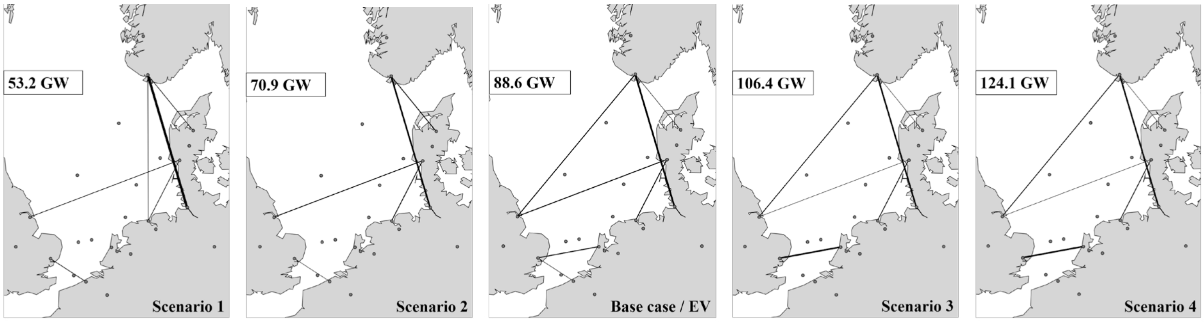

Fig. 3. The plots shows the different solutions obtained from a deterministic program for four different wind capacity scenarios, in addition to the expected value (EV) scenario, i.e. the base case. The thickness of the line plots indicate the size of the investments. Offshore wind capacity and scenario number are labeled in each plot.

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 [20]. 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 is 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.

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 [18] is given as data input for year 2030, in addition to already planned and existing infrastructure, and investment decisions regarding grid capacity are first made in year 2030 (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 case study comprise the NSOG 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 quantify the expected value of perfect information (EVPI), value of stochastic solution (VSS), and the real option value (ROV) of postponing investments.

Both existing and planned cables by 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, meaning that the arbitrage opportunities are limited for the considered candidate lines, and the focus is narrowed down to interconnector investments (cross-border links), only. Hence, 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

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

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, in terms of capacity expansion, 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 worth of investments).

A system planner that only considers a scenario analysis would probably argue that those investments that occur in all scenarios are the most robust ones (robustness analysis). In such a case, interconnectors between NO-DE, NO-DK, DK-NL, and GB-DK would score highest under such 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 deterministic solutions (perfect foresight) as shown in Table 1. That is, 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) - reflecting the value of using a stochastic program instead of a deterministic one, given the number of scenarios and probability distribution. This is, however, only an estimate.

3.2. Stochastic solution: One investment stage

With a classical two-stage formulation, i.e. without a 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 cannot 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 (see Figure 3), 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 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 with €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).

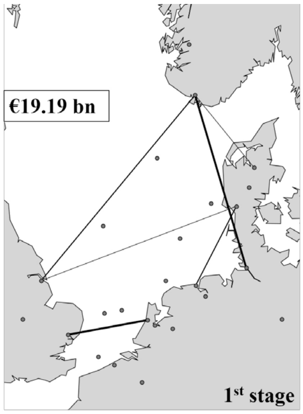

Fig. 4. Two-stage stochastic solution when only considering one investment stage (year 2030). Investment cost is given in the figure.

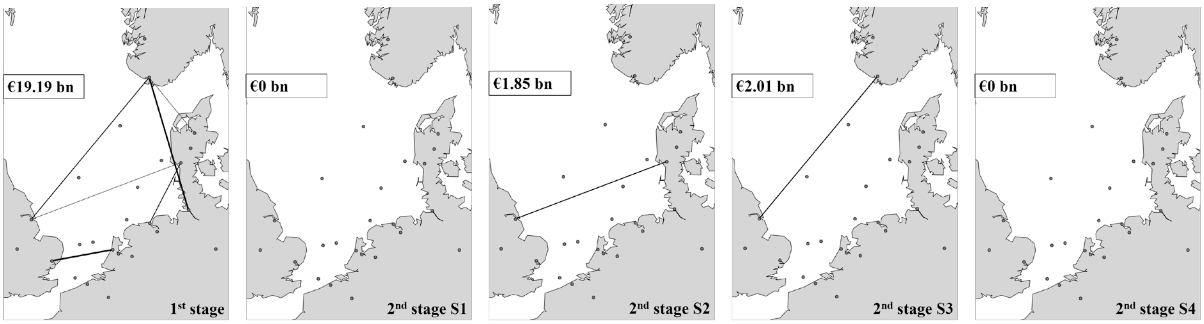

Fig. 5. Multi-stage stochastic program solutions. The first stage investments in the most-left figure, followed by second stage investments ranging from scenario 1-4. The system planner has the option to postpone investments, typically the ones that only occur in particular scenarios. Investment costs are given in the figure.

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 the decision maker is willing to pay for perfect information must be equivalent 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. Transmission capacity at 1000 MW are added in both scenario 2 and 3 at a cost of €1.85 bn and €2.01 bn, respectively. Compared with the deterministic EV strategy, we see that the second stage investments from Figure 5 represents the outliers in the deterministic solutions, i.e. the ones that only arise in one or two scenarios. For instance, 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 from 2000 MW to 1000 MW and wait to see whether scenario 3 occurs, or not, and then decide to build the remaining 1000 MW.

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 fairly counterintuitive 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 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 expected 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 is calculated to be €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 to 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 expected 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 calculated with ”wait-and-see” (deterministic) and ”here-and-now” (stochastic) optimization programs. 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 due to uncertainty about offshore wind capacity.

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 regarding 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 useful 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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The expansion planning model used for this work is called PowerGIM. PowerGIM is a open-source module under the market simulator PowerGAMA [17], which can be downloaded at bitbucket.org. The authors would like to thank the developers behind PYOMO [21] and PySP [22], in addition to Gurobi Optimization.

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