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An auction framework to integrate dynamic transmission expansion planning and pay-as-bid wind connection auctions

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Abstract

Competitive renewable energy procurement auctions are becoming increasingly prevalent. In a pay-as-bid auction, investors bid the price support required and receive that price if successful. Bidding strategy may be influenced by factors external to the auction, such as transmission expansion planning decisions. This may increase costs. In this paper, we show that integrating a pay-as-bid auction with transmission expansion planning may allow for total system cost minimisation over many time periods. This paper develops an auction mechanism and associated modelling framework to carry this out. The contributions of this framework are verified using a numerical example. Our results show that ignoring generation costs in transmission expansion planning can have economic consequences, while traditional pay-as-bid auctions can benefit from incorporating features associated with transmission expansion planning, such as multi-period optimisation. Full integration of both modelling frameworks can lead to efficiency improvements, both in terms of reduced investor rent-seeking and a more efficient deployment path.

Keywords: Renewable Energy, Electricity Transmission, Optimisation, Auction Design

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1. Introduction

To efficiently decarbonise the electricity system, competitive renewable energy procurement auctions are becoming increasingly common (European Commission, 2014; IRENA and CEM, 2015; Voss and Madlener, 2017). In this paper, we show that when a pay-as-bid auction is chosen, the outcome is potentially inefficient if transmission upgrades are required. We propose a novel auction framework to overcome this potential inefficiency which can facilitate the global optimisation of generation and network upgrade costs. This contribution integrates real-world auction mechanisms with commonly-employed transmission expansion planning frameworks, proposing a practical methodology which may aid real-world implementation.

Procurement auctions are becoming increasingly prevalent as a replacement for renewable energy feed-in tariffs (FiTs). FiTs have incentivised much renewable generation by offering an administratively-set guaranteed price. As the policymaker does not know the true generating cost, this provides an opportunity for over-remuneration and excessive policy cost. In a renewable energy procurement auction, investors compete on the price support required for deployment. Procurement auctions for renewables are prevalent in many countries including parts of the USA, Taiwan, India (Kylili and Fokaides, 2015) and Brazil (Porrua et al., 2010). Since January 2017, all new renewable energy supports in the EU must take the form (European Commission, 2014). There are many types of procurement auction (IRENA and CEM, 2015; Voss and Madlener, 2017) and in a pay-as-bid auction, investors pay the price they have bid, should their bid be successful.

Efficient deployment should minimise both the generation and network investment costs. Often, investment in the transmission network is required to facilitate the added renewables capacity. These additional costs are often unaccounted for in existing pay-as-bid auctions. This may lead to sub-optimal deployment. If deployment is determined by the auction outcome alone, transmission expansion costs are ignored and therefore may be excessive. If transmission expansion costs are considered but in a process separate to the auction procedure, bidding strategy may be influenced by these exogenous decisions, potentially increasing deployment costs.

These inefficiencies may be greater in a dynamic context. As transmission is a long-lived asset, the best decision today may be determined by its use tomorrow. Indeed, a path dependency may emerge, whereby today's deployment guides a suboptimal deployment pattern in all future time periods. In order to efficiently plan deployment in the current time period, one must thus consider expected future deployment patterns and resulting costs.

To overcome these sources of inefficiency, this paper integrates pay-as-bid auctions and transmission expansion planning. Transmission expansion costs are predicated on site-selection decisions, whilst optimal site selection decisions under a procurement auction framework are ideally incorporate transmission expansion costs. In many cases, transmission expansion planning and procurement auction frameworks are unable to incorporate this simultaneity. To overcome this, we formulate the investment decision as a multi-stage game, where policymakers wish to install a given capacity and investors in wind energy generation respond. We specify connection contract auctions as a competitive procurement auction, where transmission externalities are internalised into the bidding strategy.

Transmission costs are predicated on the collective siting decisions of all market players. We adapt a DC Optimal Power Flow (DCOPF) model to calculate these transmission costs and present a formalised auction procedure through which these costs are internalised into generator bidding strategies. We apply this modelling framework to the IEEE 24-bus test system to illustrate its application. A scenario-based methodology, drawing on the work of van der Weijde and Hobbs (2012) is proposed to take into account uncertain dynamic aspects of these spatial externalities.

This paper proceeds as follows. Section 2 offers a review of the literature and motivates the analysis and Section 3 described the methodology used to model the pay-as-you-bid auction frameworks considered in this paper. The remainder of this paper provides a proof of concept, applying this framework to a stylised case study example. Section 4 outlines the assumptions and data employed for this numerical application. Each step of the procedure is analysed in turn to demonstrate the overall contribution of this framework in Section 5. Some concluding comments are offered in Section 6.

2. Literature Review and Motivation

This section presents the literature review. We first review recent research in the field of renewable energy procurement auctions, observing that existing auction formats focus on internal generation costs alone, ignoring network costs and presenting the possibility of inefficiency. Relevant research in the field of transmission expansion planning is then reviewed. We find that, when a pay-as-bid auction is present, there is a need to incorporate revealed generation costs in transmission planning decisions. We conclude that these isolated approaches present the possibility of suboptimal deployment decisions, motivating the need for an integrated transmission expansion and procurement auction framework.

2.1. Contribution to pay-as-bid auction design

Pay-as-bid and uniform price structures are the most commonly employed renewable energy procurement auction types (IRENA and CEM, 2015; Voss and Madlener, 2017). In both auction structures, investors bid the price they are willing to accept per unit of electricity generated. In a pay-as-bid auction, this price is received upon successfully winning a tender.[1] This presents the investor with a trade-off; a higher bid leads to increased revenue upon winning but there is a lower

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[1] In a uniform price auction, all generators receive the most expensive successful bid (i.e. the marginal price).

probability of success. As Naert and Weverbergh (1978) and Hao (2000) discuss, rational bidders will seek to maximise utility derived from profits based on their private information, including their perception of how others will bid. Bidders may thus seek a markup by bidding in excess of their private breakeven costs. A Nash equilibrium will result when each bidder chooses a strategy and no bidder wishes to change their strategy (Hao, 2000).

The optimal bid may be influenced by factors that affect the probability of success. Under certain circumstances, increased uncertainty can increase bid markup (Voss and Madlener, 2017; Farrell and Devine, 2015). Transmission Expansion Planning (TEP) may provide such uncertainty if investors believe that TEP findings may influence site selection subsequent to the auction. Alternatively, TEP considerations may be ignored altogether by the pay-as-bid auction framework. This would remove the influence on bid formation, however, it presents the possibility of a sub-optimal spatial distribution with excessive transmission upgrade costs.

Integrating transmission upgrade costs into a pay-as-bid auction may overcome these deficiencies. The correct way to integrate transmission costs into generator decision-making is the subject of an extensive field of research. Shirmohammadi et al. (1996) discuss a number of ‘transmission pricing paradigms’ that may guide efficient generation and transmission investment. Studies by both (Shirmohammadi et al., 1996) and the subsequent literature have stated that upgrade cost apportionment amongst generators should reflect the benefit of long term incremental investment costs (Dupont et al., 2014; Commission, 2011; Hogan, 2011; Munasinghe and Warford, 1982; Ortega et al., 2008; Shirmohammadi et al., 1996; Tabors, 1994; Shahidehpour et al., 2002).

2.2. Contribution to Transmission Expansion Planning Literature

Given the relevance of Transmission Expansion Planning to efficient pay-as-bid auction design, integrating Transmission Expansion Planning (TEP) and pay-as-bid auctions provides a timely contribution to the TEP literature. Transmission Expansion Planning (TEP) models quantify the cost of transmission upgrade. TEP determines where, how many and when new devices must be added to a network in order to make its operation viable for a pre-defined horizon of planning, at a minimum cost (Hemmati et al., 2014). In general, these models identify the optimal network structure given an exogenously determined schedule of demand and supply (see, for example, Shirmohammadi et al., 1996; Brandstatt et al., 2011; Dupont et al., 2014; Hemmati et al., 2014).

Much of the TEP literature examines deployment in a centrally-planned framework (e.g. Hemmati et al., 2016; Ugranli and Karatepe, 2014), where a system operator has perfect information and controls investment decisions. Augmentations to this basic premise are often made to assist renewable energy-related decision-making. Chase et al. (2001) use weighted checklist and Data Envelopment approaches, respectively, to rank suitable sites according to qualitative, site-specific factors. Geographic Information Systems (GIS) and geospatial optimisation techniques have been employed as an alternative approach to rank site suitability (see Sklenicka and Zouhar, 2018; Ramachandra and Shruthi, 2007; Baban and Parry, 2001; van Haaren and Fthenakis, 2011; Phillips and Middleton, 2012). While providing an important step towards internalising site-specific factors into transmission planning, these centrally-planned approaches rely on perfect knowledge of internal generating costs. As has been discussed in Section 2.1, generating costs may be subject to bias if revealed via a separate pay-as-bid auction.

In liberalised markets, generators and transmission network operators make independent investment decisions guided by price signals. If the market is competitive the correct price signal should guide privately-motivated investment decisions towards the socially-optimal, least-cost solution. Therefore, the modelling problem is the same as that of a central planner with perfect information. This approach has been used by Munoz et al. (2017) to investigate the effects of risk aversion on optimal transmission and generation expansion planning. Similarly, van der Weijde and Hobbs (2012) analyse the case of a proactive transmission planner who makes investment decisions in two time periods, each followed by an investment response in a competitive environment. While pay-as-bid auction results could provide an input to this transmission expansion modelling framework, the pay-as-bid values would still be subject to potential bias in bid values, discussed in Section 2.1.

A number of TEP models have relaxed the perfectly competitive assumption to consider investor-transmission planner interactions, however, pay-as-bid procurement auctions are not assessed. Tor et al. (2008) evaluate TEP and generation planning together, assuming costs are known and planned. Whilst the strategic interaction in a pay-as-bid context is not considered, the optimal TEP and generation investment strategy over the planning horizon is identified and proposed as a guide for investors. Gu et al. (2012) and Roh et al. (2007) develop frameworks that iterate between generation and transmission expansion planning models. This emulates the interaction between generation companies and transmission companies in many markets, however it does not consider interaction with pay-as-bid auctions, as outlined in Section 2.1. Sauma and Oren (2006) consider various market structures, finding that proactive transmission planning can be welfare-improving relative to a reactive strategy, however full integration of both processes is not considered.

This review shows that while a number of papers give important insight into strategic and dynamic transmission upgrade (Hendrik van der Weijde and Hobbs, 2011; Munoz et al., 2017; Gu et al., 2012; Ng et al., 2006; Sauma and Oren, 2006), the case of competitive renewables procurement under a pay-as-bid structure is not considered. This is of increasing importance as these auction mechanisms grow in use (IRENA and CEM, 2015; Newbery, 2016; European Commission, 2014).

Indeed, this paper complements an emerging literature in this field relating to the co-optimisation of transmission and generation decisions. Alayo et al. (2017) and Spyrou et al. (2017) demonstrate that co-optimisation can have quantifiable economic consequences whilst Moreira et al. (2017) explore co-optimisation of generation and transmission with respect to reserve provision. This paper adds to this emerging literature by considering the implications and proposing a practical approach for such co-optimisation when there is a pay-as-bid auction in place. Integrating such a policy mechanism into a TEP framework would therefore be an important and timely contribution to the TEP literature, provided by this paper.

3. Methodology

In this section, we outline our methodology which models a multi-stage pay as bid auction framework. The methodology is similar to that proposed in Farrell and Devine (2015) in that it also considers a policymaker's and generators' optimisation problems. However, in contrast to Farrell and Devine (2015), the present work also incorporates a TEP optimisation model. Each of these optimisation problems are outlined in this section. Section 3 is structured as follows: firstly, in Section 3.1, we present the policymaker's optimisation problem. Secondly, in Section 3.2, we describe the generators' optimal bidding strategy both when transmission costs are internalised and when they are not. Thirdly, in Section 3.3, we specify the TEP optimisation model considered in this work. Finally, in Section 3.4, we describe the overall framework, which combines the three different optimisation problems. The model sets, variables and parameters are respectively outlined in Tables 7 - 9 in Appendix A.

3.1. Policymaker's optimisation problem

The policymaker[2] seeks to minimise the expected discounted sum of total social costs throughout all time periods ($E[TSC]$), subject to meeting wind deployment targets for each time period t. As van der Weijde and Hobbs (2012) highlight, policymakers must consider deployment over many time periods, as single period deployment may create a path dependency and result in suboptimal deployment in subsequent time periods. Future policy targets are uncertain and may be represented by a scenario ($s \in S$). The target varies across scenarios when $t > 1$, therefore the parameter $Q_{t=1}^{\text{Target}}$ represents the target that must be met in the first time period (scenario-independent) while $Q_{t,s}^{\text{Target}}$ represents the target that must be met for all subsequent time periods (scenario-dependent).

The deployment target is met by accepting n bids. We assume that there are $N > n$ wind generating sites and there is only one wind generator/investor at each site. Thus, we assume there are N bids submitted to the policymaker in total.

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[2] Throughout this paper we refer to the policymaker as the entity that makes the deployment decisions. This entity may be a transmission system operator, market operator or some other body.

A spatial arrangement must be chosen by the policymaker to meet the targets. For $t = 1$ the policymaker chooses a spatial arrangement $a_{t=1}$. For $t > 1$ the policymaker must also choose a spatial arrangement $a_{t,s}$ to meet the targets for each of the different target capacity scenarios. These two variables are subsets of the set A which represents all potential sites. The policymaker's deployment decision may be formally represented as

$$\min_{a_{t=1}, a_{t,s} \in A} E[TSC] \tag{1}$$

subject to:

$$\sum_{i \in a_{t=1}} Q_i = Q_{t=1}^{\text{Target}}, \tag{2}$$

$$\sum_{i \in a_{s,t}} Q_i = Q_{t,s}^{\text{Target}}, \ \forall s, t \in T, \tag{3}$$

$$a_{t=1} \cap a_{t,s} = \emptyset \ \forall s, t \in T, \tag{4}$$

$$a_{t,s} \cap a_{t',s} = \emptyset \ \forall s \in S, t \in T, t' \in T \backslash \{t\}, \tag{5}$$

where Q_i, a parameter, represents the capacity at site i. Constraint (2) ensures the scenario-independent target is met for time-period $t = 1$ while constraint (3) ensures that the targets for all other time periods are met for each scenario. Constraints (4) and (5) ensure that, under each scenario, if a site is chosen in one time period it cannot be chosen in another time period. The expected total societal costs, $E[TSC]$, differ depending on whether external transmission costs are internalised into generators' bids.

If external transmission upgrade costs are paid by the generators, then the policymaker's objective function is

$$E[TSC] = \sum_{i \in a_{t=1}} \sum_{t=1}^{\bar{T}} e^{-rt} k_i G_i + \sum_{\substack{s \in S \\ t \in T \\ i \in a_{t,s}}} \sum_{t'=t}^{t+\bar{T}-1} pc_s e^{-rt'} k_i G_i, \tag{6}$$

where pc_s represents the probability associated with scenario s and r represents the discount rate. The parameter $\bar{T}$ represents the number of years site i will enter a contract with the policymaker for[3]. The parameter G_i represents the yearly generation associated with site i, which is assumed fixed. The variable k_i represents the price that the generator at site i is willing to receive per unit

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[3] This value is the same for each site chosen regardless of when the site is chosen. For example, if site i is chosen for time period $t = 1$ then their contract would run from $t = 1$ to $t = \bar{T}$. If site i is chosen for time period $t = 2$ then their contract would run from $t = 2$ to $t = \bar{T} + 1$.

of electricity.

If external costs are not paid by the generator then the total societal costs may be defined as:

$$E[TSC] = \sum_{i \in a_{t=1}} \sum_{t=1}^{\bar{T}} e^{-rt}(k_i G_i + d_{i,t,a_t}) + \sum_{\substack{s \in S \\ t \in T \\ i \in a_{t,s}}} \sum_{t'=t}^{t+\bar{T}-1} pc_s e^{-rt'}(k_i G_i + d_{i,t',a_{t,s}}), \tag{7}$$

where $d_{i,t,a_{t=1}}$ and $d_{i,t,a_{t,s}}$ represent the transmission costs associated with site i in time period t if $i \in a_{t=1}$ or if $i \in a_{t,s}$, respectively. Section 3.3 and 3.4 describe how these costs are determined.

3.2. Generator's optimisation problem

In this section, we describe the generators' optimal bidding strategy and the probability that their optimal bids will be accepted, both when transmission costs are internalised and when they are not, but optimised by a separate TEP model.

3.2.1. Bidding strategy with internalised transmission costs

If the transmission costs are paid by the generators, then profit for installation at site i (π_i) is be defined as

$$\pi_i = pa_i \big[\sum_{t=1}^{\bar{T}} e^{-rt}(k_i G_i - d_{i,t,a_{t=1}}) - F_i \big], \tag{8}$$

where pa_i represents the probability of generator i's bid being accepted. The specific pa_i function under in this framework is described in detail in Section 3.2.2. It is a function of generator i's bid k_i relative to all other bids and is assumed independent to the distribution of other sites' bids. The probability of bid acceptance is the probability of their bid being accepted for time $t = 1$. We abstract from repeated bidding strategies and interdependent bids and refer to Voss and Madlener (2017) for insight into this dynamic.

The parameter F_i corresponds to the internal cost for site i and is defined as follows:

$$F_i = CQ_i + \sum_{t=1}^{\bar{T}} e^{-rt} OQ_i, \tag{9}$$

while C and O are parameters representing the capital and operating costs (€/MW) respectively.

Generator i will submit a bid k_i to maximise discounted expected profit. Assuming a concave function[4], the optimal bid is obtained when

$$\frac{\partial \pi_i}{\partial k_i} = 0. \tag{10}$$

Consequently, when transmission costs are internalised into the investor's bid, the optimal bid is:

$$k_i = \frac{F_i + \sum_{t=1}^{\bar{T}} e^{-rt} d_{i,t,a_{t=1}}}{\sum_{t=1}^{\bar{T}} G_i e^{-rt}} - \left[\frac{\partial pa_i}{\partial k_i}\right]^{-1} pa_i. \tag{11}$$

3.2.2. Probability of acceptance with internalised transmission costs

Each generator i assumes n accepted bids meet the policymaker's capacity target for time $t = 1$. When transmission costs are internalised into the generators' bidding strategy, or when there are is no TEP optimisation at all, being the n^{th} smallest bid or smaller guarantees a successful bid while being $(n+1)^{th}$ smallest bid or larger guarantees an unsuccessful bid. Thus the probability of being the n^{th} smallest bid or smaller is equal to the probability of acceptance. Under this framework expected policy cost is defined by equation (6).

Characterising the optimal bid by each generator requires information on the costs faced by generator i and the distribution of all other bids. Following the literature, we assume all other bids are drawn from a distribution with a Probability Density Function $PDF(K)$ and Cumulative Distribution Function $CDF(K)$ (Hao, 2000). Henceforth, for ease of presentation, CDF will refer to $CDF(K)$.

We define the probability that generator i's bid is less than the bid of one of the other generators as

$$P(k_i \leq K) = 1 - CDF, \tag{12}$$

Similarly, the probability that generator i's bid is greater than the bid of one of the other generators is

$$P(k_i \geq K) = CDF. \tag{13}$$

Assuming there are N independent bids in total, the probability that there is exactly $n-1$ bids less than generator i's bid and $N-1-(n-1)$ bids greater is[5]

$$\binom{N-1}{n-1}(CDF)^{n-1}(1-CDF)^{N-1-(n-1)}. \tag{14}$$

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[4] In the numerical examples described in Section 5 the generator's expected profit was found to have a concave shape (see also Farrell and Devine (2015));

[5] Note: $\binom{x}{y} = \frac{x\,!}{(x-y)\,!y\,!}$.

Furthermore the probability that there is $n-1$ or less bids less than generator i's bid is

$$\begin{aligned} pa_i(k_i) =& \binom{N-1}{n-1}(CDF)^{n-1}(1-CDF)^{N-1-(n-1)} \\ &+\binom{N-1}{n-2}(CDF)^{n-2}(1-CDF)^{N-1-(n-2)} \\ &\vdots \\ &+\binom{N-1}{1}(CDF)^{1}(1-CDF)^{N-1-(1)} \\ &+\binom{N-1}{0}(CDF)^{0}(1-CDF)^{N-1-(0)}, \end{aligned} \tag{15}$$

which is equal to

$$pa_i(k_i) = \sum_{l=0}^{n-1}\binom{N-1}{l}(CDF)^{l}(1-CDF)^{N-1-l}. \tag{16}$$

Equation (16) gives us the probability that k_i is the nth smallest bid or smaller. To specify the parameters of equation (11), the partial derivative of equation (16) with respect to k_i is required:

$$\frac{\partial pa_i}{\partial k_i} = \sum_{l=0}^{n-1}\binom{N-1}{l}\frac{\partial CDF}{\partial k_i}\Big[l(CDF)^{l-1}(1-CDF)^{N-1-l}-(N-1-l)(CDF)^{l}(1-CDF)^{N-2-l}\Big]. \tag{17}$$

In Section 4, the random bids K are assumed to follow a uniform distribution. Furthermore, in Section 5.4, we assess the bidding strategy when there is no TEP costs. The strategy follows this approach when TEP costs are internalised into the bid under the assumption that TEP costs are zero, as being the n^{th} smallest bidder or smaller guarantees success.

3.2.3. Bidding strategy with non-internalised transmission costs

If external transmission costs are not paid by the generator, but optimised by a separate TEP framework that is exogenous to the pay-as-bid auction, then the profit for the generator at site i is

$$\pi_i = pa_i\big[\sum_{t=1}^{\bar{T}} e^{-rt}k_iG_i - F_i\big]. \tag{18}$$

The pa_i function under this framework is described in Section 3.2.4. Differentiating equation (18) with respect to k_i, gives the following optimal bid:

$$k_i = \frac{F_i}{\sum_{t=1}^{\bar{T}} G_i e^{-rt}} - \left[\frac{\partial pa_i}{\partial k_i}\right]^{-1} pa_i. \tag{19}$$

3.2.4. Probability of acceptance with non-internalised transmission costs

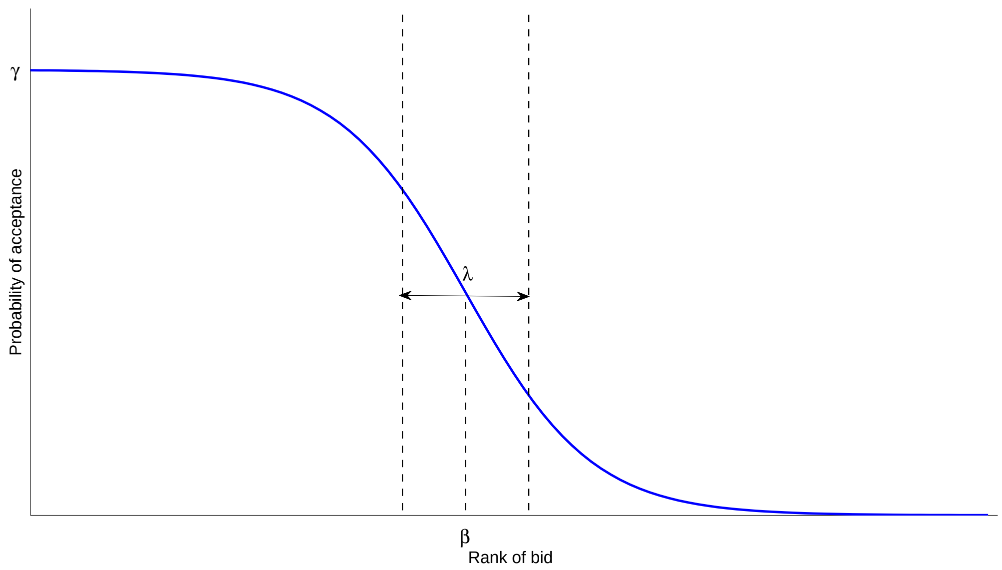
When transmission costs are not internalised into the generators' bidding strategy, but optimised by a separate TEP framework that is exogenous to the pay-as-bid auction, then being the n^{th} smallest bid or smaller does not guarantee a successful bid and policy costs are given by equation (7). As being the n^{th} lowest bid might not necessarily mean your bid gets accepted we follow a procedure similar to Brock and Durlauf (2001) and represent the probability that generator i's bid will be accepted given the rank of their bid (i.e., given there are l bids lower than theirs) by a hyperbolic tangent function:

$$pr_i(l) = \frac{\gamma}{2}(1 - \tanh(\frac{l-\beta}{\lambda})). \tag{20}$$

This function models the probability of acceptance given the rank of bid such that for low values of l there is a high probability of acceptance and similarly for high values of l there is a low probability of acceptance. A shift from the high probability regime to the low probability regime occurs over a range of magnitude λ, centered at $l = \beta$. The parameter γ ensures that the probabilities are normalised such that the expected total number of bids accepted is n, i.e., $\sum_l pr_i(l) = n$. See Figure 1 for a schematic of equation (20).

As $\lambda \to 0$, equation (20) tends towards a stepwise linear function where the probability of acceptance is equal to one when $l \leq n$ and zero when $l > n$ which results in the same situation as described in Section 3.2.2 where external costs are internalised. As $\lambda \to \infty$, equation (20) tends towards a uniform distribution such that all values of l ($0 \leq l \leq N-1$) have equal probability.

Figure 1: Probability of acceptance given the rank of bid



Using this conditional probability, the probability that generator i's bid is accepted is

$$pa_i(k_i) = \sum_{l=0}^{N-1} \frac{\gamma}{2}(1 - \tanh(\frac{l-\beta}{\lambda}))\binom{N-1}{l}(CDF)^l(1-CDF)^{N-1-l} \tag{21}$$

This probability represents the probability of being the lth ranked bid times the probability of acceptance given that rank, summed over all possible ranks. Hence, equation (21) gives us the probability of acceptance when external factors affect the ranking of successful bids. To specify the parameters of equation (19), the partial derivative of equation (21) with respect to k_i is required:

$$\begin{aligned}\frac{\partial pa_i}{\partial k_i} =& \sum_{l=0}^{N-1} \frac{\gamma}{2}(1 - \tanh(\frac{l-\beta}{\lambda}))\binom{N-1}{l}\frac{\partial CDF}{\partial k_i}\Big[l(CDF)^{l-1}(1-CDF)^{N-1-l} \\ &-(N-1-l)(CDF)^l(1-CDF)^{N-2-l}\Big].\end{aligned} \tag{22}$$

3.3. Specifying TEP costs

In this section, we specify how to calculate transmission upgrade costs, $D_{a_{t=1},a_{t,s}}$, and hence d_{i,t,a_t} portions. This is carried using a Transmission Expansion Planning (TEP) model (Soroudi, 2017). There are many different combinations that met the policy maker's target, i.e., there are many combinations for the sets $a_{t=1}$ and $a_{t,s}$. For each of these combinations, the TEP model is run obtaining a different total deployment cost ($D_{a_{t=1},a_{t,s}}$).

The TEP model used is a DC Optimal Power Flow (DCOPF) model. The model's objective is to minimise conventional transmission upgrade costs and load shedding costs subject to power generation and flow constraints, network transmission constraints in addition to energy balance constraints. The model is optimised over $|J|$ nodes/buses with $|U|$ thermal generating units. Each of the thermal generating units are associated with a node.

There are N wind generating sites in total. Each site must be located somewhere and is therefore associated with a node. The sites in the set $A_j \subset A$ are associated with node j. The amount of electricity capacity available from wind at node j (AW_j) depends on the combination of sites for $a_{t=1}$ and $a_{t,s}$ being examined. More formally:

$$AW_j = \sum_{i \in A_j \cap (a_{t=1} \cup a_{t,s})} Q_i. \tag{23}$$

With all sets, variables and parameters described in Tables 7 - 9 in Appendix A, the full optimisation problem may be defined as follows:

$$\min \ D_{a_{t=1},a_{t,s}} = \min \ inv + lsc \tag{24}$$

where

$$inv = \sum_{j,j',\tau} e^{-r\tau} \psi_{j,j',\tau} UC_{jj'} \tag{25}$$

$$x_{j,j',\tau} = X^0_{j,j'} - \Psi_{j,j',\tau} \tag{26}$$

$$\Psi_{j,j',\tau} = \Psi_{j,j',\tau-1} + \psi_{j,j',\tau} \tag{27}$$

$$lsc = \sum_{j,\tau,h} ls_{j,\tau,h} DU_h VOLL \tag{28}$$

Subject to

$$0 \leq power^G_{u,j,\tau,h} \leq P^{\max}_u \tag{29}$$

$$flow_{j,j',\tau,h} = \frac{\delta_{j,\tau,h} - \delta_{j',\tau,h}}{x_{j,j',\tau}} \tag{30}$$

$$|flow_{j,j',\tau,h}| \leq P^{\max}_{\Psi_{j,j',\tau}} \tag{31}$$

$$\sum_{j'} flow_{j,j',\tau,h} + \sum_{u} power^G_{u,j,\tau,h} + power^W_{j,\tau,h} + ls_{j,\tau,h} = VD_h(1+\tau\alpha)P^{D_0}_j \tag{32}$$

$$ls_{j,\tau,h} + power^d_{j,\tau,h} = VD_h(1+\tau\alpha)P^{D_0}_j, \tag{33}$$

$$power^W_{j,\tau,h} \leq AW_j W_h. \tag{34}$$

The transmission upgrade cost associated with the line connecting node j to j' is calculated in (25). The impedance of line connection node j to j' is updated in (26). The load shedding costs (lsc) are calculated in (28). Equation (29) defines the operational range of generators. Equations (30) to (32) represent transmission network constraints. The load shedding in node j is calculated in (33). Wind power is treated as a must-take negative load and is equal to the amount of wind available as stated in (34). The objective function plus all the constraints except constraint (30) are linear. As a result, the mode is non-linear. The proposed model is optimised over five representative snapshots (h) for each year (τ) of the planning horizon. These five snapshots represent the whole 8760 hours in a year. The representative snapshots are derived from historic data (Soroudi et al., 2017). Uncertainty modelling of wind power generation (Wang et al., 2018) is beyond the scope of this work.

3.4. Overall auction framework

Having defined the policymaker's and generators' optimisation problem, in addition to the TEP model, this section now outline the overall multi-stage auction framework. This framework provides clarity on the practical implementation for a policymaker. In order to integrate a competitive pay-as-bid auction with a TEP model, external costs must be estimated and incorporated into the bidding procedure. However, a simultaneity of outcomes exists. Exact transmission costs are determined by the collective siting of added installations whilst collective siting decisions are determined by the outcome of the auction. The simultaneity arises as transmission costs must be estimated prior to the final auction procedure for incorporation into generator bids. We propose the following multi-stage framework to address this simultaneity.

1. The policymaker sets a renewables deployment target ($Q_{t=1}^{\text{Target}}$) and seeks information regarding location and capacity of potential future deployment sites. Only location and capacity information is received at this stage and this information is used to calculate the possible combinations of sites $a_{t=1} \cup a_{t,s}$ that meets the target $Q_{t=1}^{\text{Target}} + Q_{t,s}^{\text{Target}}$.
2. There are many different possible successful combinations that may meet a policy target[6]. For each combination, the total cost of deployment ($D_{a_{t=1},a_{t,s}}$) is calculated using a TEP methodology[7].
3. For each possible combination of sites, $a_{t=1} \cup a_{t,s}$, that meets the target $Q_{t=1}^{\text{Target}} + Q_{t,s}^{\text{Target}}$ the TEP cost ($D_{a_{t=1},a_{t,s}}$) is equally disaggregated amongst sites to construct d_{i,t,a_t} and $d_{i,t,a_{t,s}}$ portions:

$$d_{i,t,a_{t=1}} = \frac{Q_i D_{a_{t=1},a_{t,s}}}{\sum_{i \in a_t \cup a_{t,s}} Q_i} \quad \text{if} \quad i \in a_{t=1}, \tag{35}$$

$$d_{i,t,a_{t,s}} = \frac{Q_i D_{a_{t=1},a_{t,s}}}{\sum_{i \in a_t \cup a_{t,s}} Q_i} \quad \text{if} \quad i \in a_{t,s}. \tag{36}$$

   As the TEP model is optimised over a number of snapshots for each year, $d_{i,t,a_{t=1}}$ and $d_{i,t,a_{t,s}}$ correspond to yearly external costs.
4. Once the TEP costs are calculated, the policymaker presents these costs to generators. Each generator then offers bids conditional on each transmission upgrade cost, as explained in Section 3.2 via equations (11) or (19)[8]. Using these submitted bids, the policymaker then

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[6] i.e., there are many combinations that could make up the sets $a_{t=1}$ and $a_{t,s}$ which are subsets of A

[7] We employ a computationally efficient TEP modelling framework to handle these numerous iterations. This is discussed in greater detail in Section 3.3. Future work will extend the model using more intensive search algorithms to apply the concept to expansion decisions with higher granularity and thus computational burden.

[8] While this presents up the possibility of speculative submissions, one may overcome this problem by putting in place a deposit mechanism or a requirement that all submissions be accompanied by a feasible deployment proposal

chooses the sites that minimise total societal costs as explained in equations (1) - (7).

The procedure as currently outlined will reliably yield a globally optimal solution. However, this brings a potentially high computational burden for implementation. In its current form, this limits the application to micro grid and small scale analysis, such as that presented by Prete and Hobbs (2016); Che et al. (2017) and Schiel et al. (2017). As the primary purpose of this paper is to provide a proof of concept for this auction framework, this is appropriate.

There is scope for efficiency improvements to widen application. For example, scenario reduction techniques, heuristic or probabilistic methods can potentially minimise the search space (Zhan et al., 2017). Other possible avenues for exploration include techniques based on high-dimensional copula theory and discrete convolution method (He et al., 2017). Testing and integrating these procedures to widen practical application may be the subject of future work. Alongside this, there may be computational savings associated with implementation. For example, it is unlikely that bids will change with marginal changes in transmission upgrade costs, reducing the number of scenarios required to be presented to investors. Indeed, a number of representative scenarios may suffice, from which a policymaker may construct a supply curve and determine the optimal deployment schedule. However, the procedure of exploring these methods and any potential efficiency/effectiveness trade-offs is outside the scope of this paper and our contribution is to propose the method upon which such testing may be built.

4. Case study: cost and bid parameters

In this section we specify the cost and bid parameters used for our case study application. A number of scenarios are used with respect to probability of future deployment outcomes and the cost of renewable energy deployment, allowing for policy-relevant phenomena to be highlighted. The case study is carried out over two time periods ($T = \{1, 2\}$). In the current period (2010-2020), the renewable penetration target of $Q^{\text{Target}}_{t=1} = 800\text{MW}$ is known with certainty. For the following period (2020-2030), the installation target is uncertain. Policymakers, however, can place a probability of there being $Q^{\text{Target}}_{t=2,s} = 0\text{MW}$, 200MW, 400MW, 800MW or 1300MW targets for the subsequent period, in addition to the $Q^{\text{Target}}_{t=1}$ target.[9] A number of scenarios are assumed in this regard. These scenarios are outlined in Table 1.

Table 2 displays cost and bid parameters values for each site, along with the number of sites considered for the analysis. We consider $N = 36$ potential wind energy generating sites. These are located at nodes 3, 17, 20 and 21, in the TEP model (see Figure 2). At each of these nodes, we

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[9] This gives a range of potential total targets (i.e. over both periods) of 800MW, 1000MW, 1200MW, 1600MW, 1800MW or 2100MW.

Table 1: Policymaker expectation scenarios: total deployment

	Probability of second period target ($Q_{t=2}^{Target}$)					
Scenario	0MW	200MW	400MW	800MW	1000MW	1300MW
1	0.5					0.5
2		0.25	0.25	0.25	0.25	
3			0.5		0.5	
4				0.33	0.33	0.33

assume there are nine sites of 100MW capacity (Q_i), which generate 2628 MWh[10] annually (G_i). Table 2 also displays cost and bid parameters values for each site The generation cost parameters follow those from Doherty and O'Malley (2011) and Farrell et al. (2017).

The λ, β and n parameters determine the influence external factors, such an exogenous transmission upgrade, may have on the probability of acceptance. These can take many values. For this application, we wish to demonstrate the potential impact choose a moderate value of influence, where $\lambda = 0.6$ and $\beta = 10$. Further insight into the impact this may have on bidding procedure, and a discussion around the sensitivity to alternate assumptions, is offered in Farrell and Devine (2015).

The upper and lower bounds for the uniform distribution of unknown bids (K) are sourced from the minimum and maximum break-even costs of generators in each cost scenario (see Tables 10 and 11), plus €5 for the upper cost limit. Where TEP costs are internalised into the bid, these are accounted for in the break even cost employed in bid range calculation.

The TEP model described in Section 3.3 is applied to the IEEE 24-bus ($J = \{1, 2, .., 24\}$) standard test case as depicted in Fig. 2 (Akhavan-Hejazi and Mohsenian-Rad, 2014). This network includes two areas with 230 kV and 138 kV sub-grids interconnected through power transformers. The total base load of this system is $\sum_j P_j^{D_0} = 2850$ MW while the generation mix includes variety of conventional technologies with $\sum_u P_u^{\max} = 3405$ MW of installed capacity (Rosso and Eckroad, 2014). It is assumed that no wind capacity pre-exists in the network. However there are $|U| = 32$ thermal units. The yearly demand growth rate (α) is assumed to be 2%.

Internal generation costs are assumed to vary depending on which node/bus they are associated with[11]. To fully explore the trade-off between line congestion and possible site-specific economies of scale, we model nodes 3 and 17 as nodes with economies of scale. We also wish to capture the use of more productive sites for small scale deployment. Therefore, economies of scale are enjoyed at all sites for small-scale deployment. Tables 10 and 11 in the appendix display the parameters used when TEP costs are not included in the analysis and when TEP costs are included in the

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[10] This value assumes a capacity factor of 30%

[11] While costs vary from node to node, sites at the same node have the same internal costs.

Figure 2: IEEE 24 bus standard test case

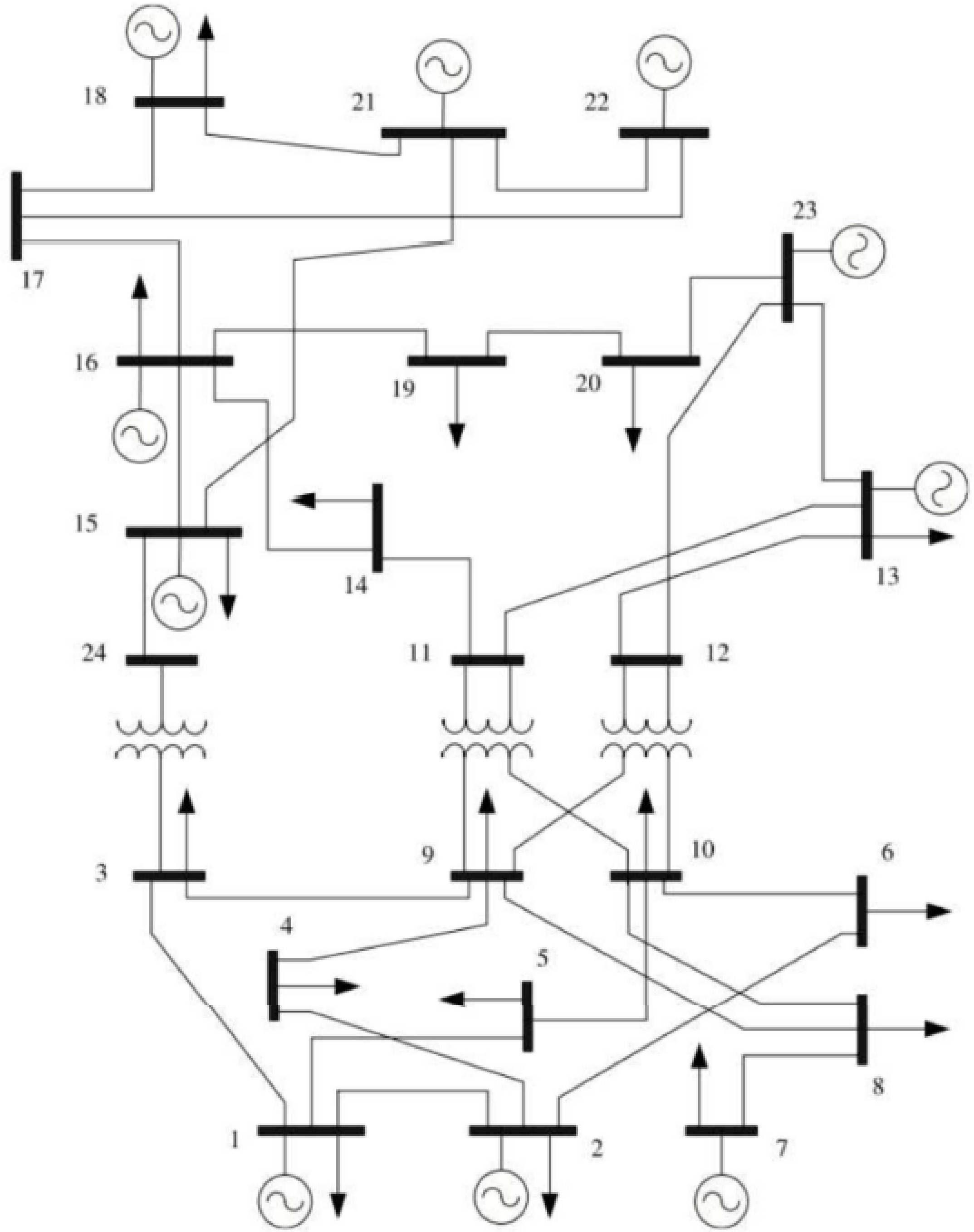


Table 2: Cost and bid parameters

Parameter	Value
Renewable site parameters	
Total number of sites (N)	36
Capacity per site (MW)	100
Nodes for renewable site location	3, 17, 20, 21
Sites (N) per node	9
Internal investment cost parameters	
Reference Capital Cost (per MW)	€1.76m
Annual operating cost (O)	2% of capital cost
Discount rate (r)	6%
Project lifetime/length of contract ($\bar{T}$)	20 years
Annual generation (per MW)	2628MWh
Bid parameters	
Influence parameter for probability of bid acceptance (λ)	0.6
Centering parameter for probability of bid acceptance (β)	10
Number of bids generators assume are accepted in first period (n)	8

analysis, respectively.

The demand, generation units and network topology data are described in Tables 12 - 14, respectively, in Appendix A. The transmission upgrade costs (Table 14) are similar to those used in Gao (2010). We adjust the figures quoted in Table 14 by a factor of ten to correspond to the cost of underground transmission lines (following findings by Hall (2013), Saastamoinen and Kuosmanen (2016) and Navrud et al. (2008)). As the IEEE 24 bus model has short line lengths relative to real world applications, assuming underground lines allows for costs to be comparable to wind generation costs. The value of loss of load ($VOLL$) is assumed to €1000/MWh. The variation of demand and wind is extracted from historic data of Irish transmission systems and it is assumed to follow the data represented in Table 15.

5. Case study: results

We apply the model setup outlined in Section 3 to illustrate the efficiency of the presented framework relative to both traditional TEP modelling and pay-as-bid auctions. We first isolate each effect, then show how they combine to impact a TEP modelling framework. We provide the following contributions:

1. We show that if external factors can affect the probability of bid success (e.g. the outcome of a TEP modelling exercise), there can be increased rent-seeking in a pay-as-bid auction.
2. We compare total costs of deployment where TEP costs are ignored (i.e. the procedure implemented by many pay-as-bid auction structures) to full integration.

3. We demonstrate the importance of a multi-period framework.
4. Relative to common alternatives, we show that full internalisation most closely approximates an optimal solution if an external influence is present.
5. We demonstrate the flexibility of practical application through a sensitivity analysis.

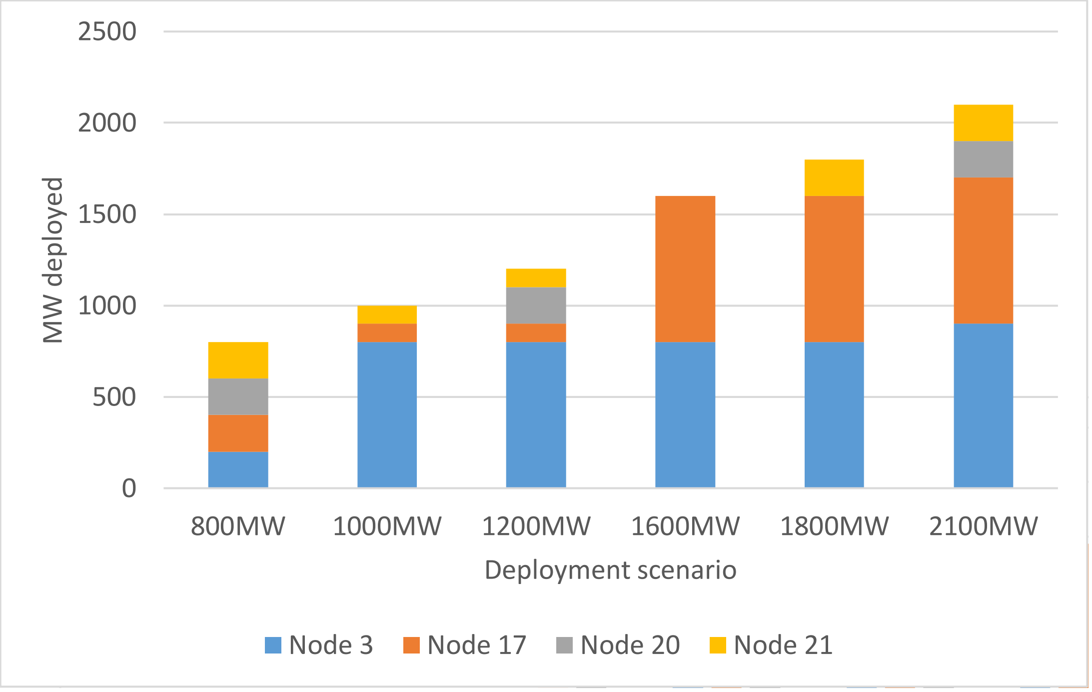
5.1. The effect of external factors on auction outcome

In this section, we examine the effect external factors, and hence bid uncertainty, has on path deployment and costs, i.e., when being the nth lowest bid or lower does not guarantee bid acceptance despite n bids being accepted. To show this clearly, we assume TEP costs are zero. We consider a deterministic time horizon; there is one decision point at time period 1 to invest in 800MW wind capacity, with the remaining capacity added after ten years (when $t = 2$). This is known with certainty. We compare the scenario of a central planner/perfect competition with the results of a pay-as-bid auction.

For this case study, we present a scenario where all deployment mechanisms (central planner, pay-as-bid with internalised transmission costs and pay-as-bid with external transmission costs) yield the same deployment outcome. The optimal deployment schedule is presented in Figure 3, where we see a distributed pattern of deployment for low installation scenarios, converging on nodes 3 and 17 for high deployment scenarios to take advantage of economies of scale. The primary contribution of this section is related to the project costs, and this is illustrated in Figure 4. For the presented case study, investors seek a mark-up of 3-5% under a pay-as-bid auction when bid uncertainty is present, relative to marginal cost. As discussed in Farrell and Devine (2015), this is because investors find the optimal point in the profit/probability of acceptance trade-off and this is often above cost.

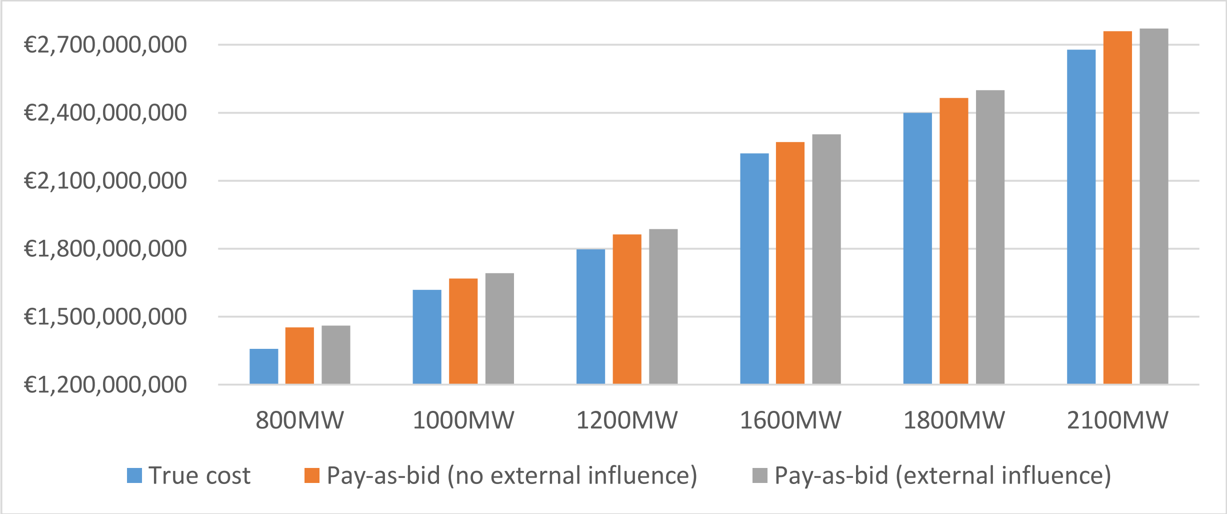
This rent-seeking is exaggerated if an external factor, such as the outcome of a TEP model affects the probability of acceptance. Investors cannot anticipate the optimal point in the profit/probability of acceptance trade-off with the same precision. Bids are inflated as investors believe there is a greater chance of successful deployment with higher bids. This leads to higher costs; figure 4 shows further cost inflation in the region 2% greater than a pay-as-bid auction where transmission costs are fully internalised into the bid. This therefore demonstrates that integrating TEP costs into the bids of a competitive pay-as-bid auctions has quantifiable economic consequences.

Figure 3: Deployment pattern for single period case study with no transmission costs



Note: Figure displays total discounted generation costs for each deployment scenario. This case study excludes transmission expansion planning costs. It is assumed that if capacity of 100MW-200MW is deployed at any node, costs are 80% of the reference value. It is also assumed that if capacity of 800MW-900MW is deployed at nodes 3 or 17, costs are 85% of the reference value. These assumptions account for favourable site selection for small-scale deployment and economies of scale associated with large scale deployment.

Figure 4: Deployment cost comparison: true cost vs. pay-as-bid



Note: Table displays total discounted generation costs for each deployment scenario. This case study excludes transmission expansion planning costs. It is assumed that if capacity of 100MW-200MW is deployed at any node, costs are 80% of the reference value. It is also assumed that if capacity of 800MW-900MW is deployed at nodes 3 or 17, costs are 85% of the reference value. These assumptions account for favourable site selection for small-scale deployment and economies of scale associated with large scale deployment.

5.2. Internalising TEP costs into bids vs. pay-as-bid auction with no TEP optimisation

The first section of Table 3 shows the deployment outcome when a pay-as-bid auction takes place and there is no transmission expansion planning. The second section showing results when TEP results are fully internalised into the investors bids in a pay-as-bid model. As expected, we see that total costs are much higher when TEP optimisation does not occur, in the region of 16-25% for this case study.

There are two factors contributing to this. As one would expect, the exclusion of transmission costs from the optimisation procedure presents the possibility of higher transmission costs in the chosen scenario, and this can be seen with respect to Table 3. However, we can also observe how this interacts with potential rent-seeking by the generator. Table 3 shows that the total cost of generation support is greater when transmission costs are not internalised than with fully internalised transmission cost.

This may be explained by additional rent-seeking. As discussed in Section 3, the generator will seek to find the optimal point in the trade-off between their cost and the cost of all other bidders. When transmission costs are not internalised, this disparity is relatively greater, and low cost generators may feel they can shade their bids to a greater extent and still win the contract, extracting greater economic rents. Internalising transmission costs reduces the relative difference in cost base for the presented case study and therefore reducing the scope for excessive rent-seeking. Both of these factors contribute to Table 3 showing a different deployment path being established if transmission costs are not internalised into the pay-as-bid auction. Compounded over a number of trading periods, this may lead to further inefficiencies through sub-optimal site selection.

Table 3: Comparing pay-as-bid auction outcomes when no transmission costs considered vs. fully-internalised transmission cost

Pay-as-bid auction: does not consider transmission costs							
Target	Node 3	Node 17	Node 20	Node 21	Gen. Cost	Trans. cost	Total cost
First deployment period (t=1)							
800	800	0	0	0	1,306	1,145	2,451
Second deployment period (t=2)							
1200	900	200	0	100	1,493	1,367	2,860
1600	900	700	0	0	1,693	1,304	2,997
1800	900	900	0	0	2,010	1,158	3,168
2100	900	900	100	200	2,185	1,166	3,351

Pay-as-bid auction: fully internalised transmission costs							
Target	Node 3	Node 17	Node 20	Node 21	Gen. Cost	Trans. cost	Total cost
First deployment period (t=1)							
800	700	100	0	0	1,234	816	2,050
Second deployment period (t=2)							
1200	700	200	200	100	1,198	1,023	2,221
1600	700	700	200	0	1,525	983	2,508
1800	700	900	200	0	1,531	1,170	2,701
2100	800	900	200	200	1,977	1,086	3,063

Note: Costs are displayed in €m. Table displays total discounted generation and transmission costs for each deployment scenario. Total targets relate to $Q_{t=1}^{Target} + Q_{t=2}^{Target}$. It is assumed that if capacity of 100MW-200MW is deployed at any node, costs are 80% of the reference value. It is also assumed that if capacity of 700MW-900MW is deployed at nodes 3 or 17, costs are 70% of the reference value. These assumptions are chosen to emulate favourable site selection for small-scale deployment and economies of scale associated with large scale deployment. In the forward-looking scenario, the policymaker expects total deployment of 1600MW, 1800MW and 2100MW to occur with equal probability of 33% (Scenario 4 in Table 1).

5.3. Testing the importance of a multi-period framework

In this section, we demonstrate the importance of incorporating future time periods in a pay-as-bid auction framework. We do this by comparing two scenarios: first, we consider a myopic policymaker who will optimise deployment of 800MW in time period 1 and disregard any future potential deployment. Any subsequent deployment (at $t = 2$) is then optimised conditional on the decision taken in the first time period.[12] We compare this to a policymaker who optimises over both time periods, conditional on the expected deployment in the subsequent time period, as formulated in Section 3.

Table 4 shows clearly that failure to consider future deployment can lead to a sub-optimal outcome. In the myopic case study, generators take advantage of economies associated with dispersed generation and minimise costs for the first period, 800MW deployment scenario. This leads to cost savings of 20% relative to the forward-looking scenario. However, total deployment costs in the subsequent period (which account for both first and second period costs) are as costly or more costly under a myopic decision than under a forward-looking outcome. This is because the myopic first period deployment has created a path dependency which leads to sub-optimal deployment in the subsequent period. When both periods are accounted for, final costs may up to 7% more expensive in the presented case study.

Interestingly, the presented case study leads to additional costs should the 1000MW scenario transpire. This is explained by the objective function, which is to minimise the weighted sum of expected costs, according to the policymaker's expectation of $t = 2$ deployment targets. In this scenario, the policymaker expects total deployment of 1000MW, 1200MW, 1600MW and 1800MW to occur with equal probability of 0.25. It is therefore optimal ex-ante to pursue a deployment path that may be more costly should the 1000MW scenario prove true as this is outweighed by potential savings associated with the 1200MW, 1600MW and 1800MW scenarios.

Table 5 shows the ex-ante weighted deployment costs under myopic and forward-looking scenarios, where we see that the expected cost of deployment in the myopic case study is 2.5% more expensive than under the forward-looking case study. The stochastic framework presented thus allows for future time periods to be appropriately weighted such that an an initial period installation may be designed to best serve policymaker expectations. This improves the efficiency of single-period pay-as-bid connection auctions as future network effects may be incorporated in current period decisions.

5.4. *Full internalisation of TEP costs most closely approximates an optimal solution if an external influence is present*

In this section we present different methods of TEP cost optimisation to show that, relative to common alternatives, full internalisation most closely approximates an optimal solution if an external influence is present. Table 6 shows the optimal deployment schedule and project cost under a number of auction formats to demonstrate this; a pay-as-bid auction where transmission costs are ignored, a pay-as-bid auction with separate transmission expansion optimisation; a

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[12] Thus, the objective function of Equation (6) is solved for $T = \{1\}$ where the time period relates to either period 1 or period 2 alone.

Table 4: Myopic vs Forward-looking deployment

No foresight

Target	Node 3	Node 17	Node 20	Node 21	Total cost (€m)
First deployment period (t=1)					
800	200	200	200	200	1,715
Second deployment period (t=11)					
1000	400	200	200	200	2,029
1200	400	200	400	200	2,344
1600	200	900	300	200	2,619
1800	700	700	200	200	2,728
2100	800	900	200	200	3,063

With foresight

Target	Node 3	Node 17	Node 20	Node 21	Total cost (€m)
First deployment period (t=1)					
800	200	600	0	0	2,041
Second deployment period (t=11)					
1000	300	700	0	0	2,060
1200	200	700	200	100	2,191
1600	700	700	200	0	2,508
1800	700	900	200	0	2,701
2100	800	900	200	200	3,063

Note: Table displays total discounted generation and transmission costs for each deployment scenario. Total targets relate to $Q_{t=1}^{Target}$ + $Q_{t=2}^{Target}$. It is assumed that if capacity of 100MW-200MW is deployed at any node, costs are 80% of the reference value. It is also assumed that if capacity of 700MW-900MW is deployed at nodes 3 or 17, costs are 70% of the reference value. These assumptions are chosen to emulate favourable site selection for small-scale deployment and economies of scale associated with large scale deployment. In the forward-looking scenario, the policymaker expects total deployment of 1000MW, 1200MW, 1600MW and 1800MW to occur with equal probability of 0.25 (Scenario 2 in Table 1).

Table 5: Weighted cost: Myopic vs. forward looking deployment

	Weighted cost
Myopic	2,430
Foresight	2,365
Myopic premium	2.7%

pay-as-bid auction with fully internalised transmission expansion costs and a central planner with perfect information.

First, we see that all auction outcomes lead to cost values in excess of that obtained under the central planner scenario. There is a clear trend of reduced costs as TEP costs are brought closer to the pay-as-bid auction framework. For the case study presented in Table 6, not optimising TEP costs increases period 1 costs by 20% relative to the central planner outcome. Moving from a scenario with no TEP costs to one with a separate TEP optimisation procedure reduces costs in the first period by 11%. For the case study presented in Table 6, period 1 costs are 7% greater when TEP costs are optimised by an external procedure than the central planner's decision. While generators cannot exploit the disparity between costs to extract rents to the same extent as when transmission costs are not optimised at all, they take advantage of the external influence impacting on the probability of bid acceptance, outlined in Section 5.1, to command additional rents. Table 6 shows that these rents can be reduced further by fully internalising these transmission costs into the investors bid. For the presented case study, the cost of a pay-as-bid auction with TEP costs internalised into the bid is only slightly in excess of the central planner's outcome. Fully internalising costs removes many of the excessive cost disparities and impacts of external influences on the probability of acceptance. In a competitive environment, this can lead to much lower rent-seeking.

Further insight may be offered by Table 6 into the implications for future deployment and any resulting path dependencies. As we move from disregarding transmission costs towards full internalisation into the bid, we see that period two deployment outcomes converge on those of the social planner. Indeed, one can see a number of differences in second period deployment when transmission costs are internalised to the scenario when they are not internalised. This may be due to differences in rent-seeking attenuating the cost signal and compounding future inefficiencies by creating further path dependencies. In general, the relative weighting of future events will dictate current period investment. Should preliminary analysis suggest that optimal path of deployment for additional capacity be different to that for the current period's target, then multi-period analysis will be more likely to lead to efficiency improvement.

5.5. Sensitivity analysis

For completeness, we compare auction outcomes across the many presented scenarios offered in this paper. This provides insight into the flexibility and thus practical applicability of this presented approach.

Each scenario represents a different policymaker belief about potential future deployment, displayed in Figure 5. We see that, regardless of the policymaker's expectation, the weighted cost of deployment is lower under a fully-internalised scenario relative to a a separate pay-as-bid

Table 6: Comparing optimal deployment across allocation methods

Pay as bid (transmission cost ignored)

Target	Node 3	Node 17	Node 20	Node 21	Total cost (€m)
First deployment period (t=1)					
800	800	0	0	0	2,451
Second deployment period (t=11)					
1000	900	100	0	0	2,860
1200	900	200	0	100	2,997
1600	900	700	0	0	3,168
1800	900	900	0	0	3,351
2100	900	900	100	200	3,580

Pay as bid (transmission cost not internalised)

Target	Node 3	Node 17	Node 20	Node 21	Total cost (€m)
First deployment period (t=1)					
800	700	100	0	0	2,156
Second deployment period (t=11)					
1000	800	200	0	0	2,604
1200	700	200	200	100	2,376
1600	700	700	200	0	2,738
1800	700	700	400	0	3,009
2100	700	700	700	0	3,375

Pay as bid (transmission cost internalised)

Target	Node 3	Node 17	Node 20	Node 21	Total cost (€m)
First deployment period (t=1)					
800	700	100	0	0	2,050
Second deployment period (t=11)					
1000	800	200	0	0	2,378
1200	700	200	200	100	2,221
1600	700	700	200	0	2,508
1800	700	900	200	0	2,701
2100	800	900	200	200	3,063

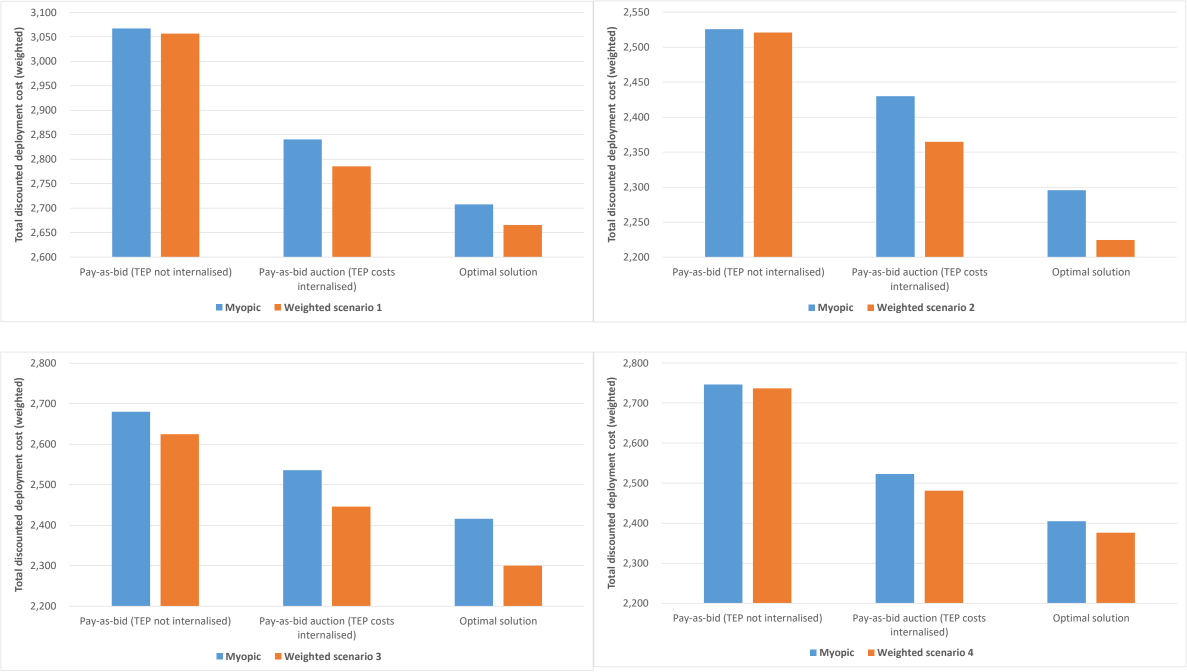
Central planner with perfect information

Target	Node 3	Node 17	Node 20	Node 21	Total cost (€m)
First deployment period (t=1)					
800	700	100	0	0	2,014
Second deployment period (t=11)					
1000	800	200	0	0	2,350
1200	700	200	200	100	2,124
1600	700	700	200	0	2,368
1800	700	900	200	0	2,591
2100	800	900	200	200	2,962

Note: Costs displayed in €m. In all scenarios, the policymaker expects total deployment targets ($Q_{t=1}^{Target} + Q_{t=2}^{Target}$) of 1600MW, 1800MW and 2100MW to occur with equal probability of 0.33 (Scenario 4 in Table 1). It is assumed that if capacity of 100MW-200MW is deployed at any node, costs are 80% of the reference value. It is also assumed that if capacity of 700MW-900MW is deployed at nodes 3 or 17, costs are 70% of the reference value.

and TEP cost-minimisation procedure. Furthermore, there are consistent benefits to adopting a forward-looking approach, as a myopic, single-period deployment horizon consistently leads to higher costs across all time periods. For the presented case study, incorporating forward-looking decision-making can lead to cost reductions in the order of magnitude of 2-3%. However, it is the internalisation of transmission upgrade costs into the bid that consistently yields the greater efficiency improvement, yielding up to 10% cost savings relative to a scenario where transmission expansion planning is carried out separate to a pay-as-bid auction. Therefore, the auction approach presented to integrate transmission costs is of practical importance for policymakers who wish to implement a pay-as-bid auction.

Figure 5: Sensitivity analysis: Auction performance for varying scenarios of expected future deployment



Figures show sensitivity of total cost to choice of policymaker expectation. Each subfigure represents a scenario outlined in Table 1

6. Conclusion

In this paper, we have proposed an auction framework to integrate pay-as-bid connection auctions with transmission expansion planning. This allows generators to reveal their private installation costs to policymakers such that both internal generation and transmission upgrade costs may be minimised. We have also presented an integrated two-stage optimisation framework, and outlined how this may be implemented for real-world application.

A number of efficiency improvements have been demonstrated through case study illustration.

First, many pay-as-bid wind connection auctions optimise deployment for a single period. However, present-day deployment may impact the cost of future deployment through . The analysis shows that multi-stage optimisation captures these future period effects and is shown to improve efficiency of allocation.

Pay-as-bid auctions are often carried out independently of transmission expansion planning. this analysis shows that quantifying and internalising transmission expansion planning costs into pay-as-bid auctions guides more socially-efficient investment decisions, should a pay-as-bid auction be chosen by a policymaker.

This paper has shown that full integration using the proposed framework leads to greater efficiency improvements than separate methodologies. First of all, greater rent-seeking is shown to occur when TEP and pay-as-bid frameworks are separate. The influence of a TEP optimisation procedure that is outside of the auction framework may lead to greater rent-seeking by generators, inflating bids and the costs of deployment.

A stylised example has highlighted the design features of commonly implemented policy mechanisms that drive inefficiencies and illustrated how the proposed auction mechanism and modelling framework may address these issues. The procedure as currently presented is suitable for small-scale deployment or inter-regional consideration, with proposed efficiency improvements potentially widening the scope to wider application. The insight offered by this paper is important for policymakers who are considering a pay-as-bid auction framework and may be a determinant in choosing between pay-as-bid or uniform price auctions. Should policymakers wish to employ a pay-as-bid auction, ignoring multi-period deployment requirements can lead to path-dependencies whereby current period investment decisions lead to suboptimal future deployment paths, whilst separate TEP and renewable capacity auctions have potential to lead to excessive rent-seeking and sub-optimal deployment. The proposed auction framework can provide efficiency improvements over more traditionally-employed pay-as-bid procedures.

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Appendix A

Table 7: Sets

Sets for auction framework	
$s \in S$	Set of target capacity scenarios
$i \in A$	Set of all possible sites
$a_{t=1} \subset A$	Sites chosen by policymaker at $t = 1$
$a_{t,s} \subset A$	Sites chosen by policymaker at $t > 1$ and scenario s
$t \in T$	Set of timesteps after time period $t = 1$
$t' \in T \backslash \{t\}$	Set of timesteps after time period $t = 1$ excluding time t
Sets for TEP model	
$u \in U$	Set of thermal generating units
$j, j' \in J$	Set of network nodes/buses
$\tau \in \mathcal{T}$	Set of years
$h \in H$	Set of snapshots

Table 8: Variables

Variables for auction framework	
$E[TSC]$	Expected total societal costs (€)
k_i	Generator at site i's bid (€/MWh)
pa_i	Probability generator i's bid is accepted
$d_{i,t,a_{t=1}}$	Yearly external costs for site i at time t for combination of sites in $a_{t=1}$ (€/MW)
$d_{i,t,a_{t,s}}$	Yearly external costs for site i at time t for combination of sites in $a_{t,s}$ (€/MW)
$a_{t=1} \subset A$	Sites chosen by policymaker at $t = 1$
$a_{t,s} \subset A$	Sites chosen by policymaker at $t > 1$ and scenario s
$pr_i(l)$	Probability generator i's bid is accepted given that their bid is the lth lowest ranked
Variables for TEP model	
$D_{a_{t=1},a_{t,s}}$	Total deployment costs associated with sites $a_{t=1}$ and $a_{t,s}$ (€)
inv	Investment costs (€)
lsc	Load shredding costs (€)
$x_{j,j',\tau}$	Electrical impedance of bus j to bus j' at year τ
$\psi_{j,j',\tau}$	% of upgrade for line between bus j to bus j' at year τ
$\Psi_{j,j',\tau}$	% of commulative upgrade for line between bus j to bus j' at year τ
$ls_{j,\tau,h}$	Load shedding at bus j year τ and time step h (MW)
$power^G_{u,j,\tau,h}$	Power produced by thermal generating unit u at bus j at year τ and time step h (MW)
$flow_{j,j',\tau,h}$	Power flow between bus j to bus j' at year τ and time step h (MW)
$power^W_{j,\tau,h}$	Power produced by wind generating units at bus j at year τ and time step h (MW)
$power^d_{j,\tau,h}$	Active power demand in bus j at year τ and time step h (MW)

Table 9: Parameters

Parameters for auction framework	
Q_i	Capacity at site i (MW)
G_i	Annual generation at site i (MWh)
$Q_{t=1}^{\text{Target}}$	Target for installed capacity at time $t = 1$ (MW)
$Q_{t,s}^{\text{Target}}$	Target for installed capacity at time $t > 1$ and scenario s (MW)
pc_s	Probability for capacity target scenario s
r	Yearly discount rate (%)
$\bar{T}$	Length of contract (years) policymaker and generator
F_i	Internal costs for site i (€)
C	Capital cost of building wind generation (€/MW)
O	Yearly operational cost for wind generation (€/MW)
$N = \|A\|$	Number of generators/investors
n	Number of accepted bids that generators assume
K	Random variable for distribution of unknown bids(€/MW)
β	Centering parameter for pr_i
λ	Level of influence ranking has on pr_i
γ	Normalisation parameter for pr_i
Parameters for TEP model	
AW_j	Available wind power generation at bus j (MW)
$VOLL$	Value of loss of load (€/MWh)
$P_j^{D_0}$	Active Power demand in bus j (MW)
$P_u^{\max}$	Maximum limit of power generation for thermal unit u (MW)
$P_{\psi_{j,j'}}^{\max}$	Maximum allowed power limit of transmission for line associated with $\psi_{i,j'}$ (MW)
$X_{j,j'}^0$	Initial % electrical impedance of bus j to bus j'
$UC_{j,j'}$	Unit cost of upgrading line between node j to node j' (€)
α	Yearly demand growth rate (%)
DU_h	Duration of time step h (hours)
W_h	Availability of wind at time step h (%)
VD_h	Percentage of peak demand at time step h (%)

Table 10: Capital costs (C) per node and installed capacity - no TEP cost scenarios (Costs quoted as % of reference value of €1.76/MW)

	100MW-200MW	300MW-700MW	800MW-900MW
Node 3	80%	100%	85%
Node 17	80%	100%	85%
Node 20	80%	100%	100%
Node 21	80%	100%	100%

Table 11: Capital costs (C) per node and installed capacity - with TEP cost scenarios (Costs quoted as % of reference value of €1.76/MW)

	100MW-200MW	300MW-600MW	700MW-900MW
Node 3	80%	100%	70%
Node 17	80%	100%	70%
Node 20	80%	100%	100%
Node 21	80%	100%	100%

Table 12: The demand data of IEEE- 24 bus network (MW)

Node j	$P_j^{D_0}$
1	108
2	97
3	180
4	74
5	71
6	136
7	125
8	171
9	175
10	195
13	265
14	194
15	317
16	100
18	333
19	181
20	128

Table 13: The thermal unit location and capacity

Generator (u)	Node (j)	$P_u^{\max}$
1	1	20
2	1	20
3	1	76
4	1	76
5	2	20
6	2	20
7	2	76
8	2	76
9	7	100
10	7	100
11	7	100
12	13	197
13	13	197
14	13	197
15	15	12
16	15	12
17	15	12
18	15	12
19	15	12
20	15	155
21	16	155
22	18	400
23	21	400
24	22	50
25	22	50
26	22	50
27	22	50
28	22	50
29	22	50
30	23	155
31	23	155
32	23	350

Table 14: The network technical data (IEEE- 24 bus)

Node j	Node j'	$X^0_{j,j'}$	$UC_{j,j'}$	$P^{\max}_{\psi_{j,j'}}$
1	2	0.0139	3.6210	175
1	3	0.2112	55.0185	175
1	5	0.0845	22.0126	175
2	4	0.1267	33.0059	175
2	6	0.192	50.0168	175
3	9	0.119	31.0000	175
3	24	0.0839	21.8563	400
4	9	0.1037	27.0143	175
5	10	0.0833	21.7000	175
6	10	0.0605	15.7605	300
7	8	0.0614	15.9950	175
8	9	0.1651	43.0092	175
8	10	0.1651	43.0092	175
9	11	0.0839	21.8563	400
9	12	0.0839	21.8563	400
10	11	0.0839	21.8563	400
10	12	0.0839	21.38563	400
11	13	0.0476	105.6766	300
11	14	0.0418	92.8000	300
12	13	0.0476	105.6766	300
12	23	0.0966	214.4612	300
13	23	0.0865	192.0383	300
14	16	0.0389	86.3617	400
15	16	0.0173	38.4077	300
15	21	0.0245	54.3923	600
15	24	0.0519	115.2230	300
16	17	0.0259	57.5005	400
16	19	0.0231	51.2842	300
17	18	0.0144	31.9694	300
17	22	0.1053	233.7761	300
18	21	0.0129	28.6392	600
19	20	0.0198	43.9579	600
20	23	0.0108	23.9770	600
21	22	0.0678	150.5225	300

Table 15: Variability of demand-wind for the case study over 8760 hours.

Snapshot (h)	D_h (%)	W_h (%)	DU_h (hours)
1	100	100	876
2	60	50	1752
3	80	80	3504
4	50	90	1752
5	70	60	876