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

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Abstract: Efficient renewables deployment requires the minimisation of both internal generation costs and external transmission expansion planning (TEP) costs. Competitive pay-as-bid connection auctions allow wind energy generators to reveal their costs of generation such that internal generation costs may be minimised. TEP costs have not been incorporated into such auctions to date. Integrating these procedures may allow for a global minimisation of internal generation and external TEP costs 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 has quantifiable economic consequences, while traditional pay-as-bid auctions can benefit from incorporating features associated with TEP, such as multi-period optimisation. Full integration of both modelling frameworks leads to efficiency improvements, both in terms of reduced investor rent-seeking and a more efficient deployment path.

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1. Introduction

The ambition to achieve an environmentally sustainable, cost-efficient and secure future energy supply has motivated greater use of renewable resources such as wind for electricity generation (E.C., 2007; DCENR, 2010; DECC, 2011). Renewables deployment requires public support as the cost of generation is often greater than the market price of electricity so far. Policymakers thus wish to minimise these costs in order to achieve efficient renewables deployment. Total social costs of renewables deployment comprises both internal investment costs (capital, operation, maintenance, etc.), alongside any incurred external costs. Given the dispersed nature of many renewable sources, such as wind, transmission system upgrade is often required.

To date, separate methodologies have been employed to minimise each of these costs. Estimation of transmission expansion costs may be carried out as part of a Transmission Expansion Planning (TEP) model. Transmission expansion planning costs are not directly related to individual deployment decisions but rather the electricity system as a whole. TEP determines where, how many and when new devices can 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). Both determinstic, single period expansions have been considered, alongside stochastic, multi-period expansion. van der Weijde and Hobbs (2012) have demonstrated that transmission expansion should be carried out in a multi-period context, using a stochastic framework to consider future uncertainty regarding system investment decisions. In practice, transmission planners do not know the private costs faced by generators and decisions made by a proactive transmission planner based on estimated or homogeneous generation costs may be subject to bias and thus inefficiency (Farrell and Devine, 2015).

On the other hand, competitive pay-as-bid auctions have been shown to incentivise investors to reveal their site-specific generation costs such that a least-cost portfolio of renewables may be deployed (Kylili and Fokaides, 2015; Farrell and Devine, 2015). TEP, to date, has not incorporated the differentiated costings facilitated by a pay-as-bid auction. Integrating these frameworks may thus allow for more efficient network expansion.

Internalising dynamic TEP costs into a pay-as-bid auction requires knowledge of collective site-selection decisions such that TEP costs may be estimated. However, generator bids and resulting site-selection decisions are determined by TEP costs. Current modelling frameworks are unable to incorporate this simultaneity. Thus, a new modelling framework is required to integrate stochastic, multi-period TEP with competitive pay-as-bid wind connection auctions. This paper provides this contribution, proposing both an auction framework and modelling platform to carry this out. Auction mechanisms to efficiently allocate connection contracts have been considered in wind energy deployment, however, the means to most efficiently minimise transmission upgrade costs has not been considered in this context. We first 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 pay-as-bid 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 externalities 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 formally presents the problem faced by a Transmission System Operator, providing a framework through which a cost minimisation procedure may be enacted. Section 4 we propose an auction methodology to carry this out. Section 5 outlines the assumptions and data employed for a numerical application to demonstrate the efficiency gains of the multi-stage procedure proposed in this paper. Each step of the procedure is analysed in turn to demonstrate the overall contribution of this framework in Section 6. Some concluding comments are offered in Section 7.

2. Literature Review and Motivation

Efficient renewables deployment requires minimisation of both internal generation and external costs, including environmental costs and transmission upgrade costs. The minimisation of transmission cost externalities is carried out by Transmission Expansion Planning (TEP) models. This literature has evolved in its treatment of how wind investment interacts with transmission expansion. Initially, much of this literature has considered wind investment decisions in a centrally-planned framework (e.g. Hemmati et al., 2016; Ugranli and Karatepe, 2014), where Transmission System Operators (TSOs) dictate locational deployment.

However, generation capacity in liberalised electricity markets is determined by private investment decisions (van der Weijde and Hobbs, 2012; Munoz et al., 2014). While transmission expansion has in many cases taken a reactive attitude to accommodate locational investment decisions (Munoz et al., 2014), recent advances in the TEP literature have focussed on using transmission planning to steer the generation market towards potentially better social outcomes. This may be achieved by forward-looking analysis and consideration as to how investors react to a given transmission investment. A number of TEP models have considered such investor-transmission planner interactions (Gu et al., 2012; Munoz et al., 2014; Ng et al., 2006; Roh et al., 2007; Sauma and Oren, 2006; Tor et al., 2008; van der Weijde and Hobbs, 2012).

However, in these works, perfect knowledge of the costs for investors in renewable energy generation has been assumed known. In reality, in many markets the internal costs of generators are not known to those charged with assigning renewable contracts and the resulting transmission investments. This information asymmetry between generators and planners may lead to a sub-optimal allocation of connection contracts. Information asymmetries may be overcome if generators signalled their internal investment costs. This may be facilitated by a pay-as-bid auction, whereby investors in renewable energy generation declare the price required for viable deployment (Kylili and Fokaides, 2015). However, to date, a pay-as-bid auction has not been integrated with TEP.

In this paper, we propose a new modelling framework that integrates a stochastic multi-period

TEP with a competitive pay-as-bid connection auction. Determining TEP costs requires knowledge of collective site-selection decisions which are determined from generators' bids. However, these bids may be affected by TEP costs, resulting in a simultaneity of outcomes in site selection. Current modelling frameworks are unable to incorporate this simultaneity. This paper proposes an iterative auction and accompanying TEP modelling procedure to identify and internalise transmission costs into competitive pay-as-bid auctions. To specify this auction framework, the generator-transmission planner relationship and deployment problem must be analysed formally. This is carried out in the following section.

3. Problem formulation

Table 1: 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

	Variables for auction framework
$E[TSC]$	Expected total societal costs (€/MW)
k_i	Generator at site i's bid (€/MW)
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 (€)
$x_{j,j'}$	Electrical impedance of bus j to bus j'
$\psi_{j,j'}$	% of upgrade for line between bus j to bus j'
ls_j	Load shedding at bus j (MW)
$power^G_{u,j}$	Power produced by thermal generating unit u at bus j (MW)
$flow_{j,j'}$	Power flow between bus j to bus j' (MW)
$power^W_j$	Power produced by wind generating units at bus j (MW)
$power^d_j$	Active power demand in bus j (MW)

Table 3: 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 (MWh)
$P_u^{\max}$	Maximum limit of power generation for thermal unit u (MWh)
$P_{\psi_{j,j'}}^{\max}$	Maximum allowed power limit of transmission for line associated with $\psi_{i,j'}$ (MWh)
$X_{j,j'}^0$	Initial % electrical impedance of bus j to bus j'
$UC_{j,j'}$	Unit cost of upgrading line between node j to node j' (€)

We follow Farrell and Devine (2015) and consider a competitive pay-as-bid auction for the allocation of wind connection contracts. Under a competitive pay-as-bid auction, generators reveal the price at which they are willing to generate electricity and receive this price if successful. This price is a signal for policymakers to choose the least-cost schedule of deployment.

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. We also assume that there are N generating sites. At each site we assume there is one investor willing to generate wind electricity. Hence we assume there are N wind energy generators/investors.

TEP and pay-as-bid connection auctions may be carried by separate, independent processes or together in an integrated procedure. When fully integrated, external costs are revealed by the policymaker and internalised into the generators' bid. When these objectives are minimised using separate procedures, a pay-as-bid auction elicits relative costs faced by generators, focussing on costs internal to the investor's decision. We formulate the policymaker's problem and generators' response considering both of these frameworks in the sections that follow.

3.1. Policymaker's problem

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. Policymakers thus wish to meet a wind deployment target for each time period t, subject to minimising the expected discounted sum of total social costs throughout all time periods, $E[TC]$. As future policy targets are uncertain, the target varies across scenarios when $t > 1$. 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 index $s \in S$ represents the different target capacity scenarios.

A spatial arrangement must be chosen by the policymaker to meet these targets. For $t = 1$ the policymaker chooses a spatial arrangement $a_{t=1}$. For $t > 1$ the policymaker must also choose

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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

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

subject to:

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

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

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

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

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 the auction and thus paid by generators. If these costs are paid by the generators, i.e. they are implicitly included in their bids, then

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

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. 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 $t = \bar{T} + 1$. The parameter G_i represents the yearly generation associated with site i, which is assumed fixed. The variable k_i represents the price generator at site i is willing to receive per unit of electricity obtained via equation (12).

If external costs are not paid by the generator then the total societal costs are

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

where $d_{i,t,a_{t=1}}$ and $d_{i,t,a_{t,s}}$ represent the external costs to be paid by site i in time period if $i \in a_{t=1}$ or $i \in a_{t,s}$ respectively. These costs are determined via the objective function of the transmission expansion model described in Section 4.2. Under this framework, the bid k_i is obtained via equation (13).

When calculating future expected costs, under both frameworks, the policymaker assumes that the bids the generators submit at time $t = 1$ are representative of bids submitted in subsequent time periods. The policymaker also assumes bids are independent. To determine the optimal schedule, the policymaker must quantify the cost of deployment, both internal costs and external costs, for each potential arrangement. To carry this out, the policymaker puts in place a pay-as-bid auction. Generators bid the €/MWh price which they require to invest at site i. This bid may include or exclude their share of transmission upgrade cost. Policymakers minimise $E[TSC]$ by choosing the least cost combination of bid and external costs. Bidding strategies under each auction specification will now be outlined.

3.2. Generator bidding strategies in a pay-as-bid auction

We adopt the modelling framework of Farrell and Devine (2015), but with the added dimension of multiple timesteps, when modelling the optimal bidding strategy of the generator. In a

competitive pay-as-bid auction, generators bid the k_i price they are willing to receive per unit of electricity generated should they win a connection contract. Policymakers choose the combination of sites from these bids that facilitates cost-minimisation. As the policymaker will offer connection contracts to the combination of sites that minimises total cost, a lower bid signals lower cost at that site and thus increases the probability of acceptance for the generator. However, a higher bid will increase the potential revenue, conditional on acceptance, as the generator will receive a higher price per unit of electricity generated. 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).

We assume generators wish to maximise their discounted expected profits. Their expected profits are the probability that their site is chosen times the discounted net money they would receive if accepted. These profits differ depending on whether external costs are paid by the generator or not. If these costs are paid by the generator then profit for installation at site i (π_i), may 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[1]. This probability is described in more detail in Section 3.2.1 and it should be noted that pa_i 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 parameter F_i corresponds to the internal cost for site i and is defined as follows:

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

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[1]As discussed in Section 4, when generators are submitting their bid, they aim for their connection contract to be accepted for time $t = 1$. Consequently their probability of acceptance is the probability of their bid being accepted for time $t = 1$.

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

If external costs are not paid by the generator then the profit for the generator at site i is

$$\pi_i = pa_i\Big[\sum_{t=1}^{\bar{T}} e^{-rt} k_i G_i - F_i\Big]. \tag{10}$$

Generator i will submit a bid k_i to maximise discounted expected profit. In the numerical examples described in Section 6 the generator's expected profit was found to have a concave shape (see also Farrell and Devine (2015)); hence their optimal bid is obtained when

$$\frac{\partial \pi_i}{\partial k_i} = 0. \tag{11}$$

Consequently, the optimal bid may be defined as

$$k_i = \frac{F_i + \sum_{t=1}^{\bar{T}} e^{-rt} d_{i,t,a_{t=1}}}{\sum_{t=1}^{\bar{T}} G_i e^{-rt}} - \Big[\frac{\partial pa_i}{\partial k_i}\Big]^{-1} pa_i, \tag{12}$$

when external costs are paid by the generators and

$$k_i = \frac{F_i}{\sum_{t=1}^{\bar{T}} G_i e^{-rt}} - \Big[\frac{\partial pa_i}{\partial k_i}\Big]^{-1} pa_i, \tag{13}$$

when external costs are not paid by the generators. Equations (12) and (13) show that when external costs are included in the generators cost, a higher bid will be submitted by the generators, all else being equal.

3.2.1. Policy cost and bidding strategy: internalised externality

Each generator i assumes n accepted bids meet the policymaker's capacity target for time $t = 1$. Under the framework where π_i includes site i's share of the total externality, being the nth 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 nth 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

$$P(k_i \leq K) = 1 - CDF, \tag{14}$$

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

$$P(k_i \geq K) = CDF. \tag{15}$$

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[2]

$$\binom{N-1}{n-1}(CDF)^{n-1}(1-CDF)^{N-1-(n-1)}. \tag{16}$$

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

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\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{17}
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[2]Note: $\binom{x}{y} = \frac{x!}{(x-y)!\,y!}$.

which is equal to

$$pa_i(k_i) = \sum_{l=0}^{n-1} \binom{N-1}{l} (CDF)^l (1-CDF)^{N-1-l}. \tag{18}$$

Equation (18) gives us the probability that k_i is the nth smallest bid or smaller. To specify the parameters of equation (12), the partial derivative of equation (18) with respect to k_i is required:

$$\frac{\partial pa_i}{\partial k_i} = \sum_{l=0}^{n-1} \binom{N-1}{l} \frac{\partial CDF}{\partial k_i} \left[l(CDF)^{l-1}(1-CDF)^{N-1-l} - (N-1-l)(CDF)^l (1-CDF)^{N-2-l} \right]. \tag{19}$$

In Section 5, the random bids K are assumed to follow a uniform distribution.

3.2.2. Policy cost and bidding strategy: externality not internalised

Under the framework where π_i does not include site i's share of external costs, then being the nth smallest bid or smaller does not guarantee a successful bid and policy costs are given by equation (7). As being the nth 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:
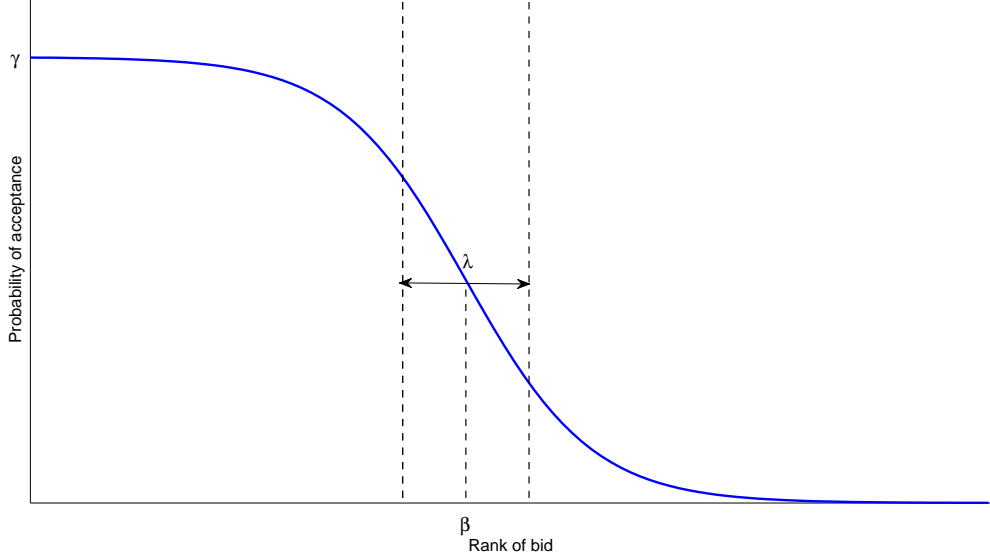
$$pr_i(l) = \frac{\gamma}{2}(1 - \tanh(\frac{l-\beta}{\lambda})). \tag{20}$$

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 3.2.1 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

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

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 (13), the partial derivative of equation (21) with respect to k_i is required:

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

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4. Solving the problem

4.1. Proposed auction framework

This paper will elicit the optimal spatial arrangement of wind connections should TEP costs be ignored; fully integrated into the auction framework; or minimised by a separate, independent methodology. 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. Initially, the policymaker sets a winds deployment target $(Q_{t=1}^{\text{Target}})$ and solicits interest from potential investors. For each potential investment, the policymaker seeks information regarding location and capacity.[3]

2. There are many different possible successful combinations that may meet a policy target[4]. For each combination, the total cost of deployment $(D_{a_{t=1},a_{t,s}})$ is calculated using a TEP methodology[5].

3. For each possible combination of sites, $a_t \cup a_{t,s}$, 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 $d_{i,t,a_{t,s}}$

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[3]While this presents 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.

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

[5]We employ a computationally efficient TEP modelling framework to handle these numerous iterations. This is discussed in greater detail in Section 4.2. 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.

portions:

$$d_{i,t,a_{t=1}} = \frac{Q_i D_{a_{t=1},a_{t,s}}}{\sum_{i \in a_t \cup a_{t,s}} Q_i} \quad \text{if} \quad i \in a_{t=1}, \tag{23}$$

$$d_{i,t,a_{t,s}} = \frac{Q_i D_{a_{t=1},a_{t,s}}}{\sum_{i \in a_t \cup a_{t,s}} Q_i} \quad \text{if} \quad i \in a_{t,s}. \tag{24}$$

As the TEP model is optimised over a single time period of one 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 (12) or (13). Using these submitted bids the policymaker then chooses the sites that minimise total societal costs as explained in equations (1) - (7).

4.2. Transmission Expansion Planning Model

To obtain the total TEP cost, $D_{a_{t=1},a_{t,s}}$, and hence d_{i,t,a_t} portions, we utilise a TEP model. As mentioned above there are many different combinations that met the policymaker'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. Similarly each of the N wind generating sites are associated with a node, which is pre-defined. 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:

$$AW_j = \sum_{i \in A_j \cap (a_{t=1} \cup a_{t,s})} Q_i. \tag{25}$$

The full optimisation problem may be defined as follows with all sets, variables and parameters described in Tables 1 - 3:

$$\min \ D_{a_{t=1}, a_{t,s}} = \min \ inv + lsc \tag{26}$$

where

$$inv = \sum_{j,j'} \psi_{j,j'} UC_{j,j'}, \tag{27}$$

$$x_{j,j'} = X^0_{j,j'} - \psi_{j,j'}, \tag{28}$$

$$lsc = \sum_j ls_j VOLL, \tag{29}$$

subject to

$$0 \le power^G_{u,j} \le P^{\max}_u, \tag{30}$$

$$flow_{j,j'} = \frac{\delta_j - \delta_{j'}}{x_{j,j'}}, \tag{31}$$

$$|flow_{j,j'}| \le P^{\max}_{\psi_{j,j'}}, \tag{32}$$

$$\sum_{j'} flow_{j,j'} + \sum_u power^G_{u,j} + power^W_j + ls_j = P^{D_0}_j, \tag{33}$$

$$ls_j + power^d_j = P^{D_0}_j, \tag{34}$$

$$power^W_j = AW_j. \tag{35}$$

The transmission upgrade cost associated with the line connecting node j to j' is calculated in (27). The impedance of line connection node j to j' is updated in (28). The load shedding costs (lsc) are calculated in (29). Equation (30) defines the operational range of generators. Equations (31) to (33) represents transmission network constraints. The load shedding in node j is calculated in (34). Wind power is treated as a must-take negative load and is equal to the amount of wind available as stated in (35). The objective function plus and all the constraints except constraint (31) are linear. As a result, the model is a non-linear. The model is also optimised over a single time period of one year. Similar TEP models can be found in (Alguacil et al., 2003; Maghouli et al., 2009, 2011)

5. Assumptions and data

5.1. Cost and bid parameters

We apply the modelling framework to a case study to illustrate the efficiencies of an integrated methodology. The case study is carried out over two time periods ($T = \{1, 2\}$). In the current period (2010-2020), the policymaker is aware that they are bound to meet a target $Q_{t=1}^{\text{Target}} = 800\text{MW}$ installation target. For the following period (2020-2030), the installation target is uncertain. Policymakers, however, can place a probability of there being $Q_{t=2,s}^{\text{Target}} = 0\text{MW}$, 200MW, 400MW, 800MW or 1300MW targets for the subsequent period, in addition to the $Q_{t=1}^{\text{Target}}$ target. We assume an equal probability ($pc_s = 0.2$) for each scenario.

We consider $N = 36$ potential wind energy generating sites. Nodes 8,11,17 and 20, in the TEP model, each have nine of these sites associated with them, with each site assuming 100MW of capacity (Q_i) and 2628MWh[6] of annual generation (G_i).

Table 4: Cost and bid parameters

Parameter	Value
Internal investment cost parameters	
Reference Capital Cost (per MW)	€1.76m
Annual operating cost (O)	2% of capital cost
Discount rate (r)	6%
Length of contract ($\bar{T}$)	20 years
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 (n)	8
Distribution of unknown bids (K)	$\mathcal{U}[60, 80]$

Table 4 displays cost and bid parameters values for each site while Table 5 shows how internal generation costs vary depending on which node/bus they are associated with[7]. The generation cost parameters follow those from Doherty and O'Malley (2011) and Farrell et al. (2013). For a more detailed discussion on the levels for the parameters associated with the probaility of acceptance (λ,

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[6]This value assumes a capacity factor of 35%.

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

β and n) see Farrell and Devine (2015). The upper and lower bounds for the uniform distribution of unknown bids (K) are chosen such that they roughly correspond to the break-even bids associated with $\pm\,20\%$ of the reference cost value of €1.76m.

Table 5 shows that nodes 8 and 11 enjoy economies of scale. Initial deployment of ≤ 200MW is carried out at a cost of 80% of the reference value quoted in Table 4, whilst deployment in excess of 800MW results in further economies of scale that lead to costs incurred being 85% of the reference value. This allows for insight into scenarios where current period deployment may not complement long-term deployment optimum and facilitates analysis which can demonstrate benefits of multi-stage analysis and gives insight into when this modelling framework may be best employed.

Table 5: Capital costs (C) per node and installed capacity (Costs quoted as % of reference value of €1.76/MW)
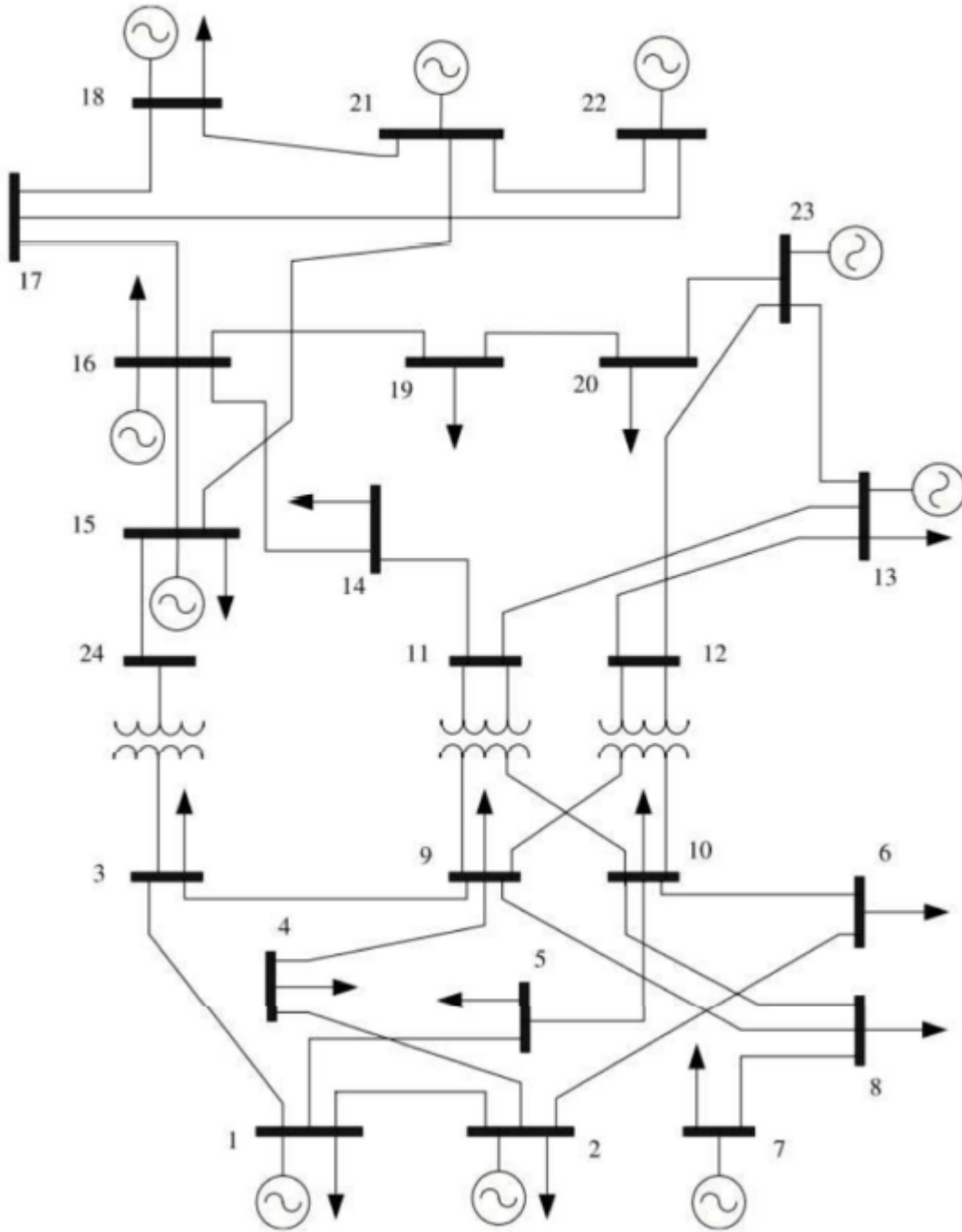
	100MW	200MW-700MW	800MW-900MW
Node 8	80%	100%	85%
Node 11	80%	100%	85%
Node 17	100%	100%	100%
Node 20	100%	100%	100%

5.2. Transmission system

The TEP model described in Section 4.2 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 (Del Rosso and Eckroad, 2014). It is assumed that no wind capacity pre-exists in the network. However there are $|U| = 32$ thermal units. 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) while the value of loss of load ($VOLL$) is assumed to €1000/MWh.

Figure 2: IEEE 24 bus standard test case

6. Case study application

We apply the model setup outlined in Sections 3 and 4 to the numerical example specified in Section 5 to illustrate the effciency improvements offered by the presented framework to both traditional TEP modelling and pay-as-bid auctions. We consider four different case studies:

1. Assuming externals costs are zero, we compare deployment as a single multi-period problem versus multiple single period problems.

2. We incorporate external costs into the pay-as-bid auction framework with external costs being paid by the generators.

3. The pay-as-bid auction is compared with a flat-rate Feed-in-Tariff.

4. We incorporate external costs into the pay-as-bid auction framework but external costs are not paid by the generators.

6.1. Importance of incorporating multi-period deployment into a pay-as-bid auction

First we test the importance of considering future time periods and, in particular, the impact explicit incorporation of uncertain future outcomes may have on future deployment paths and costs of wind deployment in a pay-as-bid auction framework. Table 6 presents results where the modelling framework is applied for multiple single periods. In this case, the policymaker is optimising their objective function for each time period independently. 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 7 shows results where both time periods are modelled together (i.e. $T = \{1, 2\}$). External costs are assumed zero and thus, the TEP model is not used in this case study.

Table 6: Naive single-period solution: external costs unaccounted for

Capacity target	Node			
$(Q_{t=1}^{\text{Target}} + Q_{t,s}^{\text{Target}})$	8	11	17	20
800MW	200	200	200	200
1000MW	400	200	200	200
1200MW	600	200	200	200
1600MW	900	300	200	200
2100MW	900	800	200	200

As both Tables 6 and 7 illustrate, second period investments must follow those of the first period. Table 6 shows that investment in a single period framework is driven by the cost efficiencies associated with installations of ≤ 200MW at each node, thus resulting in a distributed installation pattern, whilst subsequent installation is concentrated around nodes 8 and 11 to take advantage of further cost efficiencies.

Table 7: Weighted multi-period solution: external costs unaccounted for

Capacity target	Node			
$(Q_{t=1}^{\text{Target}} + Q_{t,s}^{\text{Target}})$	8	11	17	20
800MW	800	0	0	0
1000MW	800	200	0	0
1200MW	800	200	100	100
1600MW	800	800	0	0
2100MW	900	800	200	200

We see that, when multi-period investment is considered, the optimal solution is predicated on the interaction of future deployment patterns with cost drivers within the system. When potential future deployment is considered, the efficiencies gained by co-location outweigh the efficiencies of distributed generation for the presented case study. This is shown in Table 8. First period

investment is concentrated at node 8, allowing for subsequent installations to be concentrated at nodes 8 and 11, where economies of scale may be exploited. These benefits may only be reaped in the second time period and a multi-stage framework is required in order to allow for such foresight to be incorporated into current-period deployment. Thus, we see that incorporating a stochastic framework is of considerable benefit when potentially conflicting cost considerations may be incurred in relation to scale of deployment. In particular, the relative weighting of future events will dictate current period investment and 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 lead to efficiency improvement.

It should also be noted that, should time period 1 receive a considerable weighting, then the stochastic solution will converge on the deployment pattern offered in Table 6. The stochastic framework presented thus allows for future time periods to be appropriately weighted such that an appropriate initial period installation may be designed to best serve policymaker expectations. This improves the efficiency of traditionally employed single-period pay-as-bid connection auctions.

Table 8: Societal costs (millions of euro)

Capacity target ($Q_{t=1}^{\text{Target}} + Q_{t,s}^{\text{Target}}$)	Single period	Multi period
800MW	1,527	1,554
1000MW	1,817	1,782
1200MW	2,076	2,010
1600MW	2,504	2,482
2100MW	3,044	3,055
Weighted Total	2,194	2,177

6.2. Incorporating external costs into the pay-as-bid auction framework: external costs paid by the generators

To date, pay-as-bid auctions have been implemented with respect to internal generation costs alone. This case study analyses the importance of incorporating TEP costs into this framework,

employing the full procedure outlined in Section 4. Table 9 illustrates the optimal solution when external costs are internalised into the bidder's bidding strategy, i.e, when the generators' bid is determined via equation (12) and total societal costs are calculated via equation (6). Comparing these results to those of Table 7, we see that this alters the optimal multi-period deployment path. In particular, the initial 800MW investment shifts from deployment at Node 8 to Node 11. While this incurs similar first period costs, this shift facilitates second period deployment that avoids excessive transmission upgrade costs. Comparing Tables 7 and 9 we see greater distribution of deployment across nodes 17 and 20 when transmission costs are internalised. This is driven by the fact that transmission upgrade costs are often greater with greater concentration of added capacity in our case study model. This reflects many real-life scenarios where wind capacity factors may be concentrated in certain locations, and thus internal costs may motivate concentrated deployment.

Table 9: Weighted multi-period solution: internalised transmission costs

Capacity target $(Q_{t=1}^{\text{Target}} + Q_{t,s}^{\text{Target}})$	Node				Total societal cost (millions of euro)
	8	11	17	20	
800MW	0	800	0	0	1,554
1000MW	100	800	0	100	1,782
1200MW	200	800	100	100	2,010
1600MW	200	900	200	300	2,514
2100MW	800	900	200	200	3,137
Weighted total cost					2199

6.3. Comparison with flat-rate Feed-in-Tariff

One alternative to a pay-as-bid auction is a flat-rate FiT for all generation, commonly employed in many jurisdictions. This case study compares the cost of deployment under the presented integrated framework to that where a flat-rate FiT is in place, i.e., where k_i is set as a fixed flat-rate and not by equation (12) or (13). This flat rate is set at the breakeven price associated with the reference cost in Table 4. This quantifies the value of allowing generators to reveal cost heterogeneity through a pay-as-bid auction and integrating this with a TEP framework.

Table 10 shows that, when cost heterogeneity is not accounted for, transmission costs alone drive connection contract allocation. For all presented scenarios of Table 10, total societal costs

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are calculated via equation (6). However, total discounted costs are greater. Total social surplus is reduced according to two factors. First, internal generation costs are not necessarily minimised, leading to greater costs of generation than under the fully internalised scenario of Table 7. Indeed, table 10 shows that this may lead to path dependencies, with even greater divergence from the optimal path in future time periods.

Furthermore, generator surplus increases under this scenario. As all generators receive the same remuneration and some have lower costs, there is greater inframarginal rent, extending to between €8-10/MWh. Thus, TEP optimisation with no pay-as-bid auction reduces overall surplus as inefficient site selection occurs. Alongside this, there is a transfer of the remaining social surplus from the consumer to the producer. This is exaggerated in a multi-period context.

Table 10: Deployment: No pay-as-bid auction

Capacity target $(Q_{t=1}^{\text{Target}} + Q_{t,s}^{\text{Target}})$	Node				Total societal cost (millions of euro)
	8	11	17	20	
800MW	600	200	0	0	1,726
1000MW	600	200	0	200	1,984
1200MW	600	600	0	0	2,242
1600MW	600	900	0	100	2,757
2100MW	600	900	0	600	3,402
Weighted total cost					2422

6.4. Incorporating external costs into the pay-as-bid auction framework: external costs not paid by the generators

As Section 3 and Farrell and Devine (2015) highlight, separate pay-as-bid and TEP optimisation procedures may create uncertainty as to bid acceptance for the generator. In this case study we analyse the impact this uncertainty may have on deployment patterns in the problem framework outlined. In particular, we examine the framework where external costs are not taken into account in the generators' bids, i.e., their bids are determined via equation (13) and total societal costs are calculated via equation (7). We assume all generators have the same beliefs regarding the influence an external TEP modelling procedure may have on their probability of acceptance in a pay-as-bid auction.

While transmission cost integration guides more socially efficient deployment patterns, it also affects generator bidding strategy. As Section 4 outlines, generators seek a markup, and this is influenced by the probability of acceptance and the relative ranking of their bid. If generators have lower costs, they believe their bid has an ex-ante high probability of acceptance and thus may increase their markup. If outside factors affect the probability of acceptance, such as the outcome of a separate TEP model, the rank of their bid is not the sole determinant of the probability of success. Under such circumstances, generators will seek a greater markup as this uncertainty creates the belief that generators can seek a higher markup and still be amongst the successful bids. This desire to seek an additional markup is emphasised for bidders of lower costs. This has the potential to inflate bids and distort the ranking of potential bids.

Table 11 shows the outcome should all generators believe uncertainty will affect their probability of acceptance. In this case, we see that outcomes are similar as the weighted scenario of Table 7. However, we see that the re-ranking of bids has shown subtle differences in optimal deployment for 1000MW and 1200MW scenarios. All costs of deployment are greater due to higher rent-seeking.
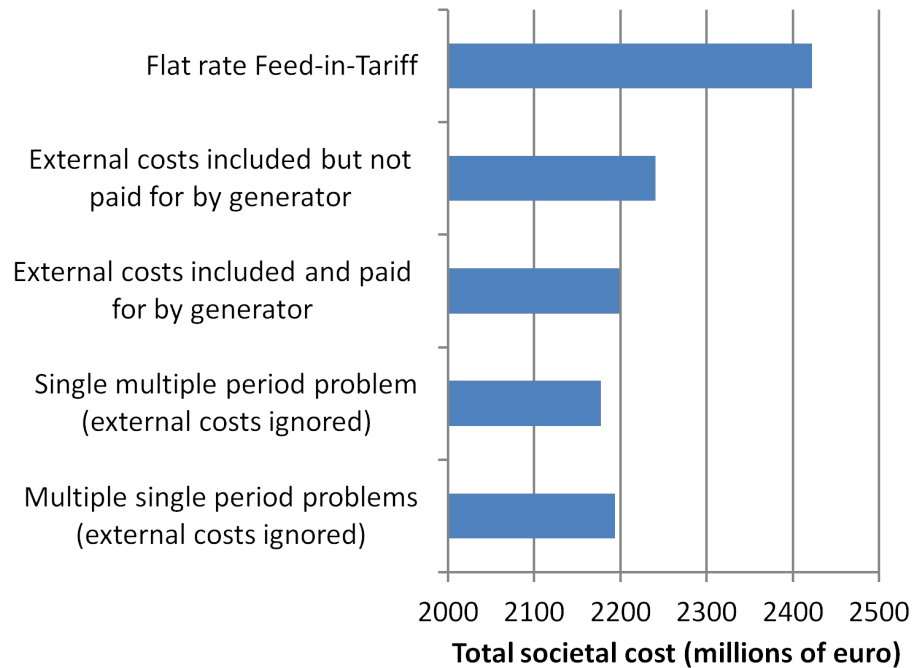
Table 11: Deployment under homogeneous expectation of uncertainty

Capacity target $(Q_{t=1}^{\text{Target}} + Q_{t,s}^{\text{Target}})$	Node				Total societal cost (millions of euro)
	8	11	17	20	
800MW	0	800	0	0	1,586
1000MW	200	800	0	0	1,819
1200MW	200	800	0	200	2,053
1600MW	300	900	200	200	2,563
2100MW	800	900	200	200	3,183
Weighted total cost					2241

6.5. *Summary of case studies*

Figure 3 compares the total societal costs for each of the case studies considered in this section. As expected, when external costs are ignored, societal coats are at a minimum. However, for many jurisdictions, this assumption is not valid.

Figure 3: Total societal cost for each case study

When external costs are included in the policy framework, Figure 3 shows that internalising external costs into generators' bids, i.e., where there is certainty in acceptance of bids, leads to a least cost solution. When the pay-as-bid auction is compared with a flat rate FiT, it is clear to see that the FiT leads to higher societal costs.

In these analyses we concentrated on the total societal costs and efficiencies in site deployment for each of the different case studies. In Farrell and Devine (2015) optimal generator bids are examined. However, as stated already, Farrell and Devine (2015) does not incorporate a TEP model.

7. Conclusion

In this paper, we have proposed an auction framework to integrate pay-as-bid connection auctions with transmission expansion planning. The purpose of this integration is to overcome information asymmetry, allowing 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, which may be used for

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case study or real-world application.

A number of efficiency improvements have been demonstrated through case study illustration. First, many pay-as-bid wind connection auctions are single period by nature. However, deployment may impact future deployment patterns. 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 TEP optimisation. The analysis shows that quantifying and internalising transmission expansion planning costs into pay-as-bid auctions guides more socially-efficient investment decisions. This is of particular importance for existing TEP modelling frameworks which do not consider cost heterogeneity. By ignoring potential information asymmetries, future transmission planning may be guided towards facilitating wind deployment that is not least cost. Indeed, generators may take advantage of informational rents should a homogeneous FiT or other such financial support exist as the analysis shows that a flat-rate FiT has the highest total societal cost of the case studies considered.

Finally, 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 methodologies are separate as uncertainty created by 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.

The purpose and scope of this paper has been to demonstrate the inefficiencies associated with commonly employed TEP and pay-as-bid auction frameworks and propose a methodology to overcome these deficiencies. A stylised example has provided a sufficient platform to carry this out, highlighting the design features of commonly implemented policy mechanisms that drive inefficiencies and illustrating how the proposed auction mechanism and modelling framework may address these issues. Further research on this topic is necessary to expand the applicability of this modelling framework by relaxing some of the assumptions employed. In particular, this model has taken the approach of van der Weijde and Hobbs (2012) and considered inter-regional transmission expansion and thus limited application to a finite number of scenarios. Future work will increase

the granularity of application, by extending the number of decision stages, deployment bundles and scenario alternatives.

Nevertheless, while this numerical example is carried out under a number of stylised assumptions, the importance of the conclusions still hold. 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 wind connection auctions have potential to lead to sub-optimal wind deployment. The proposed auction framework can provide significant efficiency improvements over more traditionally-employed allocation procedures.

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Appendix A

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

Year	Number	Title/Author(s) ESRI Authors/Co-authors *Italicised*
2015	522	Surplus Identification with Non-Linear Returns *Peter D. Lunn**and Jason J. Somerville†
	521	Water Quality and Recreational Angling Demand in Ireland *John Curtis*
	520	Predicting International Higher Education Students' Satisfaction with their Study in Ireland Mairead Finn and *Merike Darmody*
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