

Farrell, Niall; Devine, Mel T.; Soroudi, Alireza

Working Paper

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

ESRI Working Paper, No. 523

Provided in Cooperation with:

The Economic and Social Research Institute (ESRI), Dublin

Suggested Citation: Farrell, Niall; Devine, Mel T.; Soroudi, Alireza (2016) : An auction framework to integrate dynamic transmission expansion planning and pay-as-bid wind connection auctions, ESRI Working Paper, No. 523, The Economic and Social Research Institute (ESRI), Dublin

This Version is available at:

<https://hdl.handle.net/10419/129416>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

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

Niall Farrell, Mel T. Devine and Alireza Soroudi[†]*

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.

**Corresponding Author(s): mel.devine@esri.ie*

[†]Electricity Research Centre, School of Electrical, Electronic & Communications Engineering, University College Dublin.

Keyword(s): Renewable Energy; Electricity Transmission; Optimisation; Auction Design

JEL Codes:

Acknowledgements: This work was funded under the Programme for Research in Third-Level Institutions (PRTL) Cycle 5 and co-funded under the European Regional Development Fund (ERDF); Science Foundation Ireland awards 09/SRC/E1780 and 12/IA/1683. The authors would like to acknowledge the ESRI's Energy Policy Research Center, UCD's Electricity Research Center, Seán Lyons, Valentin Bertsch and James Gleeson (University of Limerick). All omissions and errors are our own.

ESRI working papers represent un-refereed work-in-progress by researchers who are solely responsible for the content and any views expressed therein. Any comments on these papers will be welcome and should be sent to the author(s) by email. Papers may be downloaded for personal use only.

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 deterministic, 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 Fokaidis, 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 $t = 1$ |
| $t' \in T \setminus \{t\}$ | 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 |

Table 2: Variables

| 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 l th 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) |
| $power_{u,j}^G$ | Power produced by thermal generating unit u at bus j (MW) |
| $flow_{j,j'}$ | Power flow between bus j to bus j' (MW) |
| $power_j^W$ | Power produced by wind generating units at bus j (MW) |
| $power_j^d$ | 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 $\psi_{j,j'}$ (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

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

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

subject to:

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

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

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

$$a_{t,s} \cap a_{t',s} = \emptyset \quad \forall s \in S, t \in T, t' \in T \setminus \{t\}, \quad (5)$$

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

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

where $p c_s$ 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

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

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

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

where pa_i represents the probability of generator i 's bid being accepted¹. 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:

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

¹As 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 $t = 1$.

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

$$\pi_i = pa_i \left[\sum_{t=1}^{\bar{T}} e^{-rt} k_i G_i - F_i \right]. \quad (10)$$

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

$$\frac{\partial \pi_i}{\partial k_i} = 0. \quad (11)$$

Consequently, the optimal bid may be defined as

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

when external costs are paid by the generators and

$$k_i = \frac{F_i}{\sum_{t=1}^{\bar{T}} G_i e^{-rt}} - \left[\frac{\partial pa_i}{\partial k_i} \right]^{-1} pa_i, \quad (13)$$

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 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

$$P(k_i \leq K) = 1 - CDF, \quad (14)$$

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

$$P(k_i \geq K) = CDF. \quad (15)$$

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 is²

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

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

$$\begin{aligned} p a_i(k_i) &= \binom{N-1}{n-1} (CDF)^{n-1} (1 - CDF)^{N-1-(n-1)} \\ &+ \binom{N-1}{n-2} (CDF)^{n-2} (1 - CDF)^{N-1-(n-2)} \\ &\vdots \\ &+ \binom{N-1}{1} (CDF)^1 (1 - CDF)^{N-1-(1)} \\ &+ \binom{N-1}{0} (CDF)^0 (1 - CDF)^{N-1-(0)}, \end{aligned} \quad (17)$$

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

which is equal to

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

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

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

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 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:

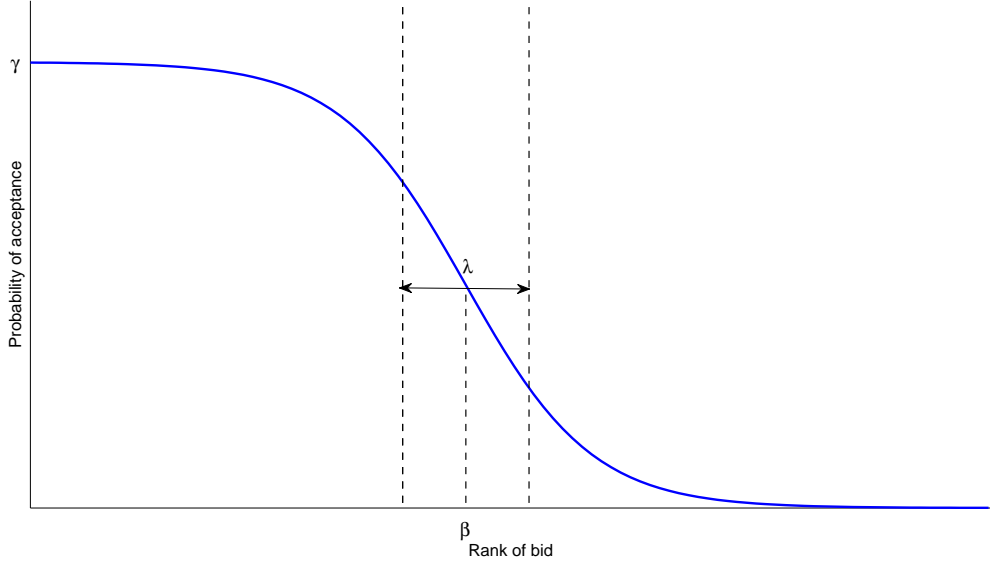
$$pr_i(l) = \frac{\gamma}{2} \left(1 - \tanh\left(\frac{l-\beta}{\lambda}\right) \right). \quad (20)$$

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 $\lambda \rightarrow 0$, 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 $\lambda \rightarrow \infty$, 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

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

This probability represents the probability of being the l th 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:

$$\frac{\partial pa_i}{\partial k_i} = \sum_{l=0}^{N-1} \frac{\gamma}{2} \left(1 - \tanh\left(\frac{l - \beta}{\lambda}\right)\right) \binom{N-1}{l} \frac{\partial CDF}{\partial k_i} \left[l(CDF)^{l-1} (1 - CDF)^{N-1-l} - (N-1-l)(CDF)^l (1 - CDF)^{N-2-l} \right]. \quad (22)$$

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 target⁴. For each combination, the total cost of deployment ($D_{a_{t=1}, a_{t,s}}$) is calculated using a TEP methodology⁵.
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 $d_{i,t,a_{t,s}}$

³While 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.

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

⁵We 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:

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

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

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 $d_{i,t,a_{t=1}}$ 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:

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

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

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

where

$$inv = \sum_{j,j'} \psi_{j,j'} UC_{j,j'}, \quad (27)$$

$$x_{j,j'} = X_{j,j'}^0 - \psi_{j,j'}, \quad (28)$$

$$lsc = \sum_j ls_j VOLL, \quad (29)$$

subject to

$$0 \leq power_{u,j}^G \leq P_u^{\max}, \quad (30)$$

$$flow_{j,j'} = \frac{\delta_j - \delta_{j'}}{x_{j,j'}}, \quad (31)$$

$$|flow_{j,j'}| \leq P_{\psi_{j,j'}}^{\max}, \quad (32)$$

$$\sum_{j'} flow_{j,j'} + \sum_u power_{u,j}^G + power_j^W + ls_j = P_j^{D_0}, \quad (33)$$

$$ls_j + power_j^d = P_j^{D_0}, \quad (34)$$

$$power_j^W = AW_j. \quad (35)$$

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 |
|---|-----------------------|
| <i>Internal investment cost parameters</i> | |
| 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 |
| <i>Bid parameters</i> | |
| 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 with⁷. 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 probability of acceptance (λ ,

⁶This value assumes a capacity factor of 35%.

⁷While 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 ≤ 200 MW 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)

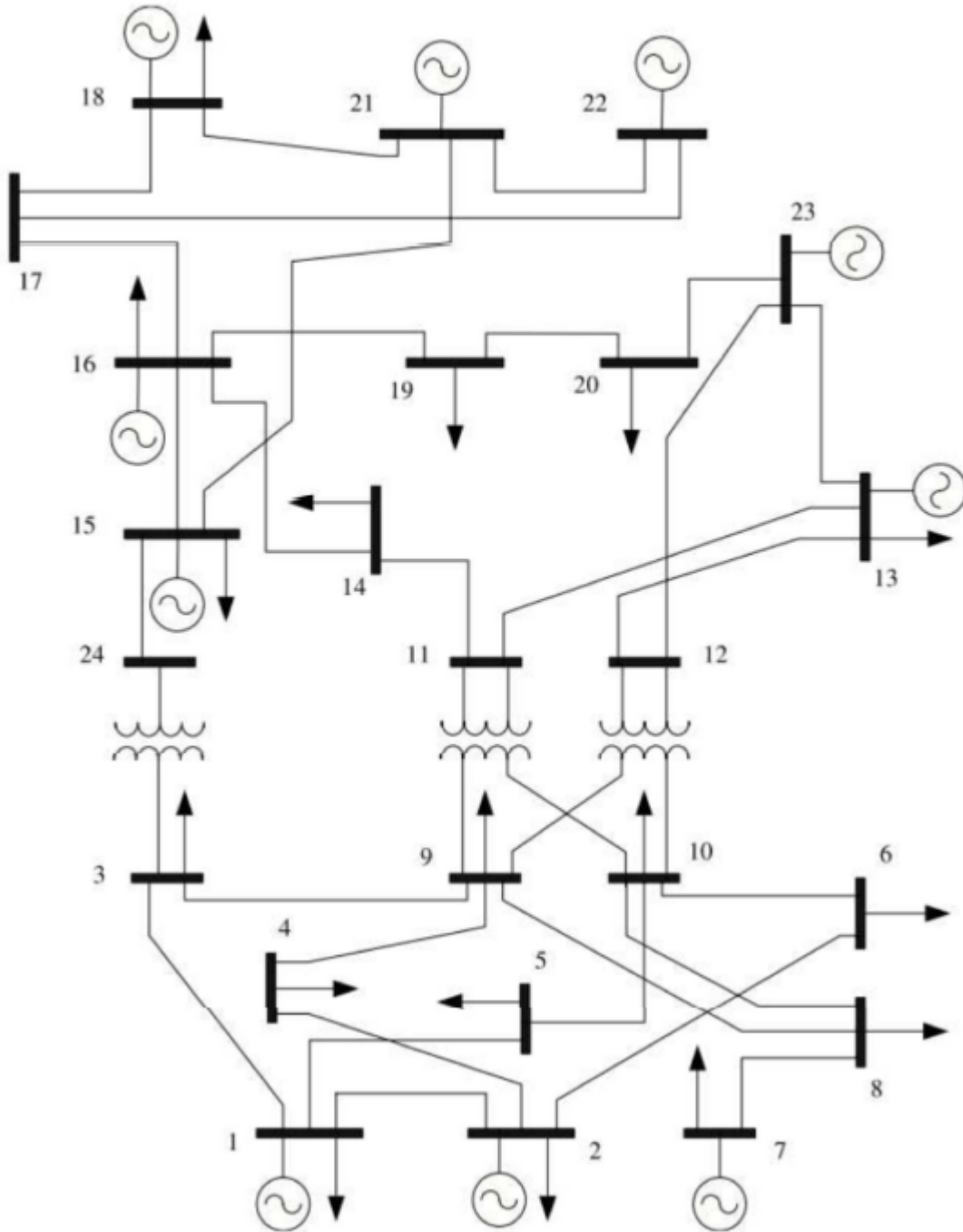
| | 100MW | 200MW-700MW | 800MW-900MW |
|---------|-------|-------------|-------------|
| Node 8 | 80% | 100% | 85% |
| Node 11 | 80% | 100% | 85% |
| Node 17 | 100% | 100% | 100% |
| Node 20 | 100% | 100% | 100% |

5.2. Transmission system

The TEP model described in Section 4.2 is applied to the IEEE 24-bus ($J = \{1, 2, \dots, 24\}$) 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 efficiency improvements offered by the presented framework to both traditional TEP modelling and pay-as-bid auctions. We consider four different case studies:

1. Assuming external 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 ($Q_{t=1}^{\text{Target}} + Q_{t,s}^{\text{Target}}$) | Node | | | |
|--|------|-----|-----|-----|
| | 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 $\leq 200\text{MW}$ 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 ($Q_{t=1}^{\text{Target}} + Q_{t,s}^{\text{Target}}$) | Node | | | |
|--|------|-----|-----|-----|
| | 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

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.

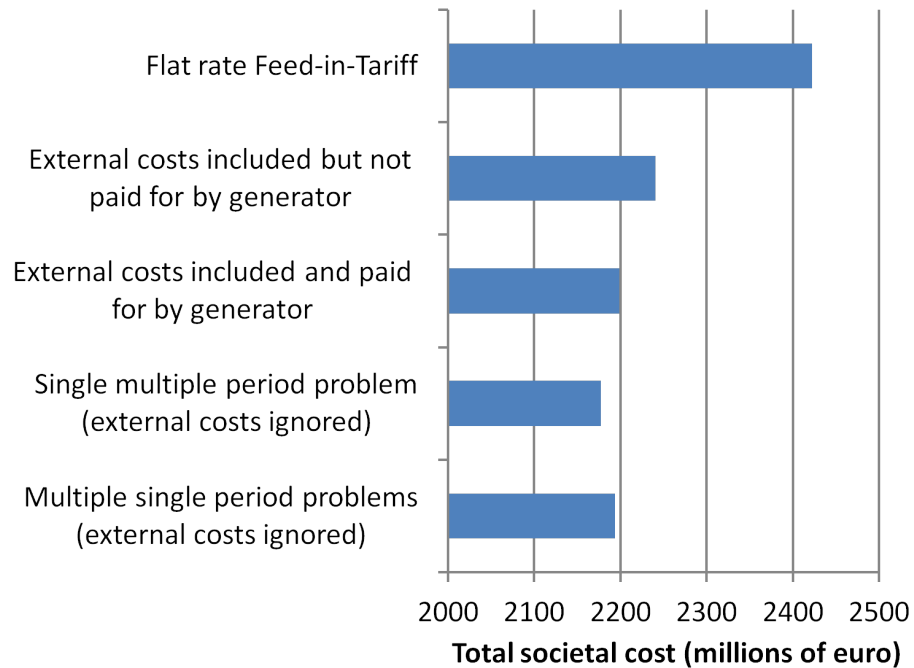
Table 11: Deployment under homogeneous expectation of uncertainty

| 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 costs 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

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.

References

Akhavan-Hejazi, H., Mohsenian-Rad, H., March 2014. Optimal operation of independent storage systems in energy and reserve markets with high wind penetration. *Smart Grid, IEEE Transactions on* 5 (2), 1088–1097.

Alguacil, N., Motto, A., Conejo, A., Aug 2003. Transmission expansion planning: a mixed-integer lp approach. *Power Systems, IEEE Transactions on* 18 (3), 1070–1077.

Brock, W. A., Durlauf, S. N., 2001. Discrete choice with social interactions. *The Review of Economic Studies* 68 (2), 235–260.

DCENR, 2010. National renewable energy action plan ireland. Tech. Rep. Submitted under Article 4 of Directive 2009/28/EC.

DECC, 2011. Uk renewable energy roadmap. Tech. rep.

URL https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/48128/2167-uk-renewable-energy-roadmap.pdf

Del Rosso, A., Eckroad, S., March 2014. Energy storage for relief of transmission congestion. *Smart Grid, IEEE Transactions on* 5 (2), 1138–1146.

- Doherty, R., O'Malley, M., 2011. The efficiency of Ireland's renewable energy feed-in tariff (refit) for wind generation. *Energy Policy* 39 (9), 4911–4919.
- E.C., 2007. *An Energy Policy for Europe*. Brussels: Office for Official Publications of the European Communities.
- Farrell, N., Devine, M., Lee, W., Gleeson, J., Lyons, S., Sep. 2013. Specifying an efficient renewable energy feed-in tariff. MPRA Paper 49777, University Library of Munich, Germany.
URL <http://ideas.repec.org/p/pramprapa/49777.html>
- Farrell, N., Devine, M. T., 2015. How do external costs affect renewable connection contract auctions? ESRI working paper, Economic and Social Research Institute, Dublin, Ireland.
URL <https://www.esri.ie/pubs/WP517.pdf>
- Gao, Y., 2010. Adequacy assessment of composite generation and transmission systems incorporating wind energy conversion systems. Ph.D. thesis, University of Saskatchewan.
- Gu, Y., McCalley, J. D., Ni, M., 2012. Coordinating large-scale wind integration and transmission planning. *Sustainable Energy, IEEE Transactions on* 3 (4), 652–659.
- Hao, S., Aug 2000. A study of basic bidding strategy in clearing pricing auctions. *IEEE Transactions on Power Systems* 15 (3), 975–980.
- Hemmati, R., Hooshmand, R.-A., Khodabakhshian, A., 2014. Market based transmission expansion and reactive power planning with consideration of wind and load uncertainties. *Renewable and Sustainable Energy Reviews* 29 (0), 1 – 10.
URL <http://www.sciencedirect.com/science/article/pii/S1364032113006023>
- Hemmati, R., Hooshmand, R.-A., Khodabakhshian, A., 2016. Coordinated generation and transmission expansion planning in deregulated electricity market considering wind farms. *Renewable Energy* 85, 620 – 630.

URL <http://www.sciencedirect.com/science/article/pii/S0960148115301142>

Kylili, A., Fokaides, P. A., 2015. Competitive auction mechanisms for the promotion renewable energy technologies: The case of the 50mw photovoltaics projects in cyprus. *Renewable and Sustainable Energy Reviews* 42 (0), 226 – 233.

URL <http://www.sciencedirect.com/science/article/pii/S1364032114008399>

Maghouli, P., Hosseini, S., Buygi, M., Shahidehpour, M., May 2009. A multi-objective framework for transmission expansion planning in deregulated environments. *Power Systems, IEEE Transactions on* 24 (2), 1051–1061.

Maghouli, P., Hosseini, S., Buygi, M., Shahidehpour, M., Feb 2011. A scenario-based multi-objective model for multi-stage transmission expansion planning. *Power Systems, IEEE Transactions on* 26 (1), 470–478.

Munoz, F. D., Hobbs, B. F., Ho, J. L., Kasina, S., 2014. An engineering-economic approach to transmission planning under market and regulatory uncertainties: Wecc case study. *Power Systems, IEEE Transactions on* 29 (1), 307–317.

Naert, P. A., Weverbergh, M., 1978. Cost uncertainty in competitive bidding models. *The Journal of the Operational Research Society* 29 (4), pp. 361–372.

URL <http://www.jstor.org/stable/3009871>

Ng, S. K., Lee, C., Zhong, J., 2006. A game-theoretic approach to study strategic interaction between transmission and generation expansion planning. In: 2006 38th Annual North American Power Symposium, NAPS-2006 Proceedings.

Roh, J. H., Shahidehpour, M., Fu, Y., 2007. Market-based coordination of transmission and generation capacity planning. *Power Systems, IEEE Transactions on* 22 (4), 1406–1419.

Sauma, E. E., Oren, S. S., 2006. Proactive planning and valuation of transmission investments in restructured electricity markets. *Journal of Regulatory Economics* 30 (3), 261–290.

Tor, O. B., Guven, A. N., Shahidehpour, M., 2008. Congestion-driven transmission planning considering the impact of generator expansion. *Power Systems, IEEE Transactions on* 23 (2), 781–789.

Ugranli, F., Karatepe, E., June 2014. Transmission expansion planning for wind turbine integrated power systems considering contingencies. In: *Innovations in Intelligent Systems and Applications (INISTA) Proceedings, 2014 IEEE International Symposium on*. pp. 350–355.

van der Weijde, A. H., Hobbs, B. F., 2012. The economics of planning electricity transmission to accommodate renewables: Using two-stage optimisation to evaluate flexibility and the cost of disregarding uncertainty. *Energy Economics* 34 (6), 2089 – 2101.

URL <http://www.sciencedirect.com/science/article/pii/S0140988312000436>

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' | $X_{j,j'}^0$ | $UC_{j,j'}$ | $P_{j,j'}^{\max}$ |
|----------|-----------|--------------|-------------|-------------------|
| 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 <i>Italicised</i> |
|------|--------|---|
| 2015 | 522 | Surplus Identification with Non-Linear Returns <i>Peter D. Lunn*</i> and Jason J. Somerville [†] |
| | 521 | Water Quality and Recreational Angling Demand in Ireland <i>John Curtis</i> |
| | 520 | Predicting International Higher Education Students' Satisfaction with their Study in Ireland Mairead Finn and <i>Merike Darmody</i> |
| | 519 | What Factors Drive Inequalities in Carbon Tax Incidence? Decomposing Socioeconomic Inequalities in Carbon Tax Incidence in Ireland <i>Niall Farrell</i> |
| | 518 | A Menu Approach to Revealing Generator Reliability Using a Stochastic Bilevel Mathematical Program <i>Mel T. Devine and Muireann Á. Lynch</i> |
| | 517 | How Do External Costs Affect Pay-As-Bid Renewable Energy Connection Auctions? <i>Niall Farrell and Mel T. Devine</i> |
| | 516 | Income-Related Subsidies for Universal Health Insurance Premia: Exploring Alternatives using the SWITCH Model <i>Tim Callan, Brian Colgan and John R Walsh</i> |
| | 514 | Review of the Droichead Pilot Programme <i>Joanne Banks, Paul Conway, Merike Darmody, Aisling Leavy, Emer Smyth and Dorothy Watson</i> |
| | 513 | Firm-Level Estimates of Fuel Substitution: An Application to Carbon Pricing <i>Marie Hyland and Stefanie Haller</i> |
| | 512 | Academic Achievement among Immigrant Children in Irish Primary School <i>Frances McGinnity, Merike Darmody and Aisling Murray</i> |