Strategic Wind Power Investment

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***Abstract*—This paper considers the problem of identifying the optimal investment of a strategic wind power investor that participates in both the day-ahead (DA) and the balancing markets. This investor owns a number of wind power units that jointly with the newly built ones allow it to have a dominant position and to exercise market power in the DA market, behaving as a deviator in the balancing market in which the investor buys/sells its production deviations. The model is formulated as a stochastic complementarity model that can be recast as a mixed-integer linear programming (MILP) model. A static approach is proposed focusing on a future target year, whose uncertainties pertaining to demands, wind power productions, and balancing market prices are precisely described. The proposed model is illustrated using a simple example and two case studies.**

***Index Terms*—Electricity market, market power, mathematical program with equilibrium constraints (MPEC), strategic producer, wind power investment.**

I. Introduction

THE installed wind power capacity throughout the world has rapidly increased in recent years [1] with the aim, among other objectives, of reducing emissions [2]. As a result, there are several regions in Europe, e.g., Denmark or Spain, in which the installed wind power capacity represents a large percentage of the total installed capacity (about 25%), and wind production represents a large portion of the total production. Moreover, wind plants are in the hands of few producers. In these regions, wind producers have attained dominant positions and participate in the electricity market under similar conditions as conventional producers do. In such market framework, wind producers may consider behaving strategically and exercising market power. This has motivated the development of offering strategies to maximize the expected profits of wind power producers [3], [4].

In this paper, we propose a strategic wind power investment model to maximize the expected profit of a strategic wind power investor. This investor already owns a number of wind units and needs to decide both the sizing and siting of the new wind units to be built. Once these new wind units have been built, the investor recovers its investment cost by selling its production in the electricity market. There exist different trading floors, e.g., the DA market, the balancing market, or the futures market. The DA market is cleared once a day, one day in advance, and on an hourly basis. The balancing market is used to compensate for the deviations between generation and demand in close time (e.g., half an hour) to the actual power delivery. Finally, futures market allows for medium and long-term transactions. Among these trading floors, we consider that the wind power investor participates strategically in the DA market, which is generally the market with the largest volume of trading, and buys/sells its production deviations in the balancing market. Since wind power production is uncertain and difficult to forecast, futures markets are generally not of interest to wind power producers.

We consider that the wind power investor has the option of investing at different sites of an existing electric energy system. Note that building wind power units at a given site is contingent to 1) the physical possibility of building wind units in such location; and 2) the wind power conditions in such place. However, network bottlenecks may play an important role in determining the maximum capacity that is optimal to build in any site. Thus, having the option of investing in different sites makes a difference under network bottlenecks.

Several wind power investment models have been proposed in the literature, e.g., [5]–[8]. However, these models do not represent the strategic behavior of the investor. Investment by strategic producers has been tackled in [9] and [10]. Nevertheless, in these references, the investment is carried out considering conventional production units. Considering stochastic production facilities, such as wind power units, requires models rather different than those pertaining to conventional units to address the uncertainty in the production of stochastic units. Note that the actual production of stochastic units is not known at the time of offering to the DA market. While the owners of conventional units can control their actual productions, wind power producers cannot. Thus, wind power producers face a significant risk. For instance, if a wind power producer offers a high production level and its actual production is finally low, such producer has to buy at a probably high price in the balancing market. This uncertainty level requires a significantly different modeling framework, such as the one proposed in this paper.

To address this problem, we propose a mathematical program with equilibrium constraints (MPEC) that allows representing both the investment decisions and the operation of the DA electricity market [11], [12].

To the best of our knowledge, no similar strategic wind power investment model has been proposed in the technical literature. Thus, the contributions of this paper are twofold:

1) To formulate a bilevel model to determine the optimal wind power investment decisions of a strategic wind power investor that participates in both the DA and the balancing markets.

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2) To analyze the results of a simple example and two case studies, which show the working and effectiveness of the proposed model.

The remaining of this paper is organized as follows. Section II provides a detailed problem description. Section III gives the proposed model formulation consisting in a bilevel model and its transformation into an MPEC. Section IV provides results from an example based on a three-node system. Section V analyzes and discusses two case studies based on the IEEE 24-node Reliability Test System (RTS) and the IEEE 118-node Test System (TS). Finally, some relevant conclusions are highlighted in Section VI.

II. Problem Description

A. Approach

We consider a strategic wind power investor whose aim is to decide the new wind power units to be built through an existing electric energy network. This investor already owns some wind power units in this system and participates in both the DA and the balancing markets. If the old and newly built units constitute a large portion of the total available capacity, the investor may be able to exercise market power and to alter market prices to its own benefit. We consider that the investor exercises its market power in the DA market, while it buys/sells its production deviations in the balancing market.

We consider that producers get paid in the DA market at the locational marginal price (LMP) of the node at which they are located; and that there is a single price for buying/selling in the balancing market, being this price constant through the system (not locational). Locational prices are usually considered in most US markets, e.g., PJM [13] and ISO-New England [14], while other markets consider uniform prices, e.g., the electricity market in the Iberian Peninsula [15]. We consider a uniform pricing mechanism in the balancing market for the sake of simplicity. Note that considering LMPs in this market is straightforward but at the cost of handling a much larger amount of data.

For this analysis, a static approach is considered, i.e., the investment and market participation of the wind investor are modeled on a future target year. A static investment approach constitutes an appropriate tradeoff between modeling accuracy and computational tractability. Static approaches are usually considered in long-term generation investment problems [9], [10]. However, note that the proposed model can be reformulated to embody a dynamic approach, as in [8] or [16]. Such dynamic approach is computationally heavier than a static one, but it can be generally tackled by decomposition [7], [8]. A dynamic approach would be the subject of future research work.

B. Uncertainty Characterization

The operation of both the DA and the balancing markets is highly influenced by the uncertainty of some parameters as explained below.

Demand and wind power production uncertainties play an important role in the DA market. Demands mainly determine the actual production of the different generation units and, consequently, the market prices; while the wind production level mainly determines the profit that the wind producer achieves.

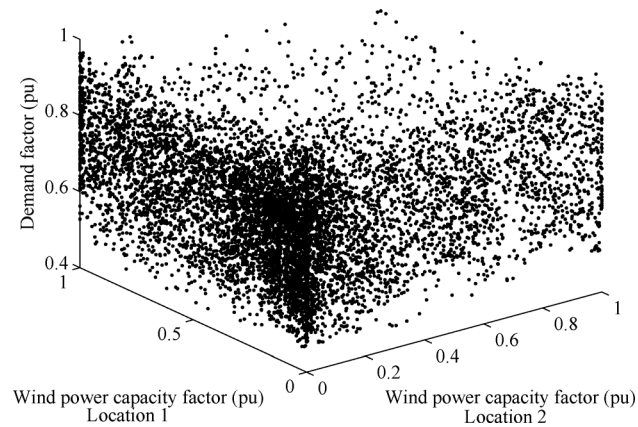

Fig. 1. Historical data of demand and wind power production conditions.

Based on the price and quantity offered to the DA market, each producer gets scheduled a production level that it must provide. The owners of production units contractually commit themselves to produce at certain power levels. Note that units (both conventional and wind-based) get assigned in the DA market specific power levels that they must provide. However, note that the DA market is cleared one day in advance and the actual wind power production is subject to uncertainty. Thus, a wind power unit may get assigned a higher/lower production than that available. In such a case, the wind power unit must buy/sell in the balancing market the difference between its assigned power and its actual production level, and pay/get paid at the corresponding balancing market price. Thus, the operation of the balancing market is highly influenced by the uncertainties in the wind production and in the balancing market price.

The uncertainty related to demand, wind production, and balancing market price is jointly modeled as described below. We consider historical hourly data throughout one or several years in the system under study. This information comprises data of demand in each demand location, data of wind production (or wind speed data) in each production location, and data of balancing market price.

As explained above, demand and wind production are the two uncertain parameters with the greatest influence on the operation of the DA market. To model this uncertainty, we use the K-means clustering method [17] to reduce the historical hourly data of demand and wind power production into a reduced set of clusters (groups) that represent different operating conditions. This reduced set of operating conditions is projected to the future target year to obtain a set of representative DA market clearing conditions, each one comprising a value of the demand in each demand location, the wind production in each production location and a weighting factor representing the number of hours that comprises this DA market clearing condition in the target year, proportional to the number of historical observations allocated to each cluster. Note that in the projection to the target year, wind speeds can be considered constant but not the demands, which usually increase. Observe also that the K-means technique allows representing both the uncertainty of and the correlation (if it exits) among the historical data of demand and wind production. A detailed description of the working of the K-means technique is provided in [17].

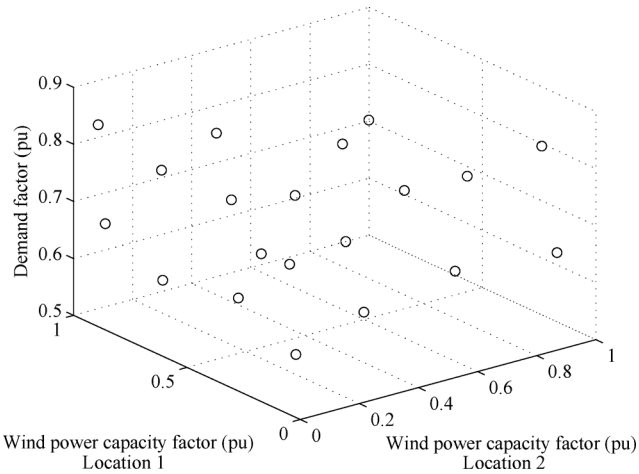

Fig. 2. DA market clearing conditions obtained using the K-means clustering technique.

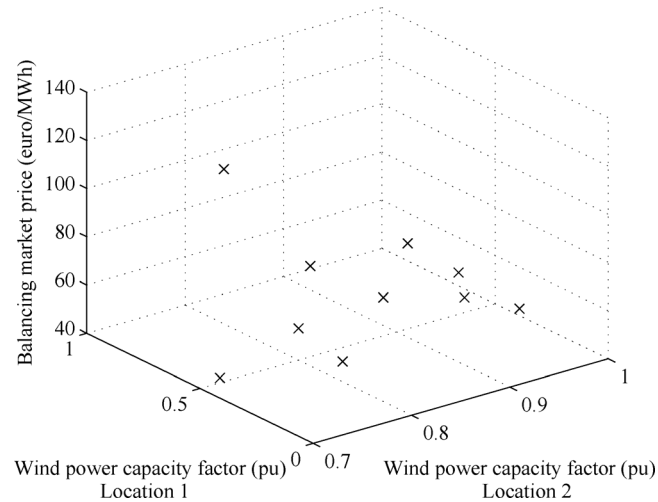

Fig. 3. Wind power production and balancing market price scenarios.

For example, Fig. 1 depicts the historical hourly data of demand factors (defined as demands values divided by the peak demand) and wind power capacity factors (defined as wind power production divided by installed wind power capacity) at two different wind locations. The K-means clustering technique is applied to this historical data set, which is reduced into a set of 20 clusters, each one defined by a value of the demand factor and a value of the wind power capacity factor in each wind location. This reduced data set is depicted in Fig. 2. Note that each of the points depicted in Fig. 2 defines a DA market clearing condition. However, the weight of each of these DA market clearing conditions is different and proportional to the number of historical observations allocated to each cluster.

The clearing of the DA market may result in that the wind producer is scheduled a higher/lower production than its actual production and thus, we need to model the operation of the balancing market for each DA market clearing condition. As stated above, the balancing market is highly influenced by the uncertainties in the wind production which affects the balancing market prices: if the wind production is high, the system generally experiences an excess of generation that usually results in a comparatively low balancing market price. On the other hand, if the wind production is low, the system generally has a deficit of generation that usually results in a comparatively high balancing market price. Thus, the uncertainties in both the wind productions and in the balancing market prices are jointly modeled following the steps below:

1) For each cluster (i.e., for each DA market clearing condition obtained using the K-means clustering technique), we consider all the historical wind power production and balancing market price observations allocated to this cluster (i.e., all wind power production and balancing market price historical data associated to the DA market clearing condition).
2) We apply the K-means clustering method to the wind production and balancing market price observations allocated to each cluster (and representing each DA market clearing condition) and obtain, for each DA market condition, a set of subclusters. Each subcluster is defined by a value of the wind production in each location and a value of the balancing market price. These values are projected to the future target year. While wind capacity factors can be considered constant, appropriate projections of balancing market prices should be considered. We consider wind capacity factors constant from year to year because they are the result of atmospheric processes contingent to the geography of the regions where the wind plants are located. However, this is not the case of prices, which are subject to economic forces and usually increase with time.
3) Each subcluster obtained in the previous step constitutes a balancing market scenario within each DA market clearing condition, and is assigned a weight equal to the number of historical observations allocated to the subcluster divided by the number of observations allocated to the corresponding DA market clearing condition.

For example, Fig. 3 depicts the balancing market scenarios associated to a particular DA market clearing condition and obtained using the method explained above. Each scenario comprises a value of the wind power capacity factor in each location, a value of the balancing market price, and has a weight that is computed as explained in step 3) above.

The balancing market is highly influenced by a number of uncertain parameters including wind production, demand, rivals' offers, and others. However, from the point of view of a wind power producer, the most influencing parameters are the wind power production and the balancing market price uncertainty. It is important to note that we use historical data to model the uncertainty in the balancing market. This way, we effectively represent the uncertainty of all involved parameters. Finally, note that the proposed model is general and additional sources of uncertainty could be included by construing comparatively more complex scenarios.

Note that the only sources of uncertainty considered are demands, wind power productions, and balancing market prices. However, the proposed model is flexible enough and additional sources of uncertainty can be included.

C. Decision Sequence

The wind investor aims at maximizing the expected profit it gets by participating in both the DA and the balancing markets,

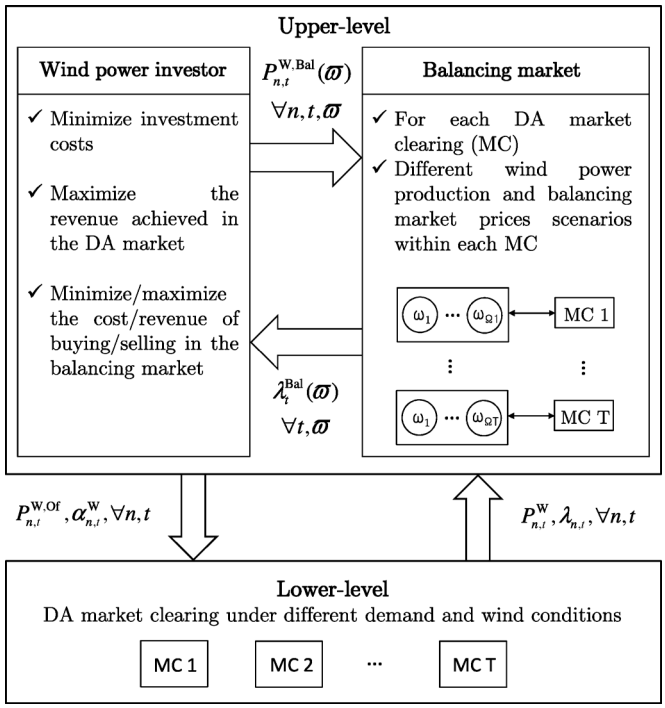

Fig. 4. Problem structure.

while minimizing its investment cost. First, it decides both the siting and sizing of the wind units to be built. Then and considering both the old and the newly built units, the investor decides the production level and the price to be offered to the DA market for each DA market clearing condition. Based on this offer information, as well as on the offers of the remaining market participants, the DA market is cleared and the investor gets scheduled a production level in this market. After that and once the investor knows its actual wind production, it buys/sells its production deviations in the balancing market at the corresponding balancing market price.

To tackle this problem, we propose a bilevel model. Fig. 4 illustrates the interactions between the wind investor and both the DA and the balancing markets. This bilevel model comprises an upper-level (UL) problem that represents the maximization of the expected profit of the wind investor; and a set of lower-level (LL) problems that represent the DA market clearing for each DA market clearing condition. For each of these conditions, the wind investor submits a wind production offer $(P_{n,t}^{\mathrm{W,Of}}, \forall n, \forall t)$ and an offer price $(\alpha_{n,t}^{\mathrm{W}}, \forall n, \forall t)$; and obtains the scheduled wind production $(P_{n,t}^{\mathrm{W}}, \forall n, \forall t)$ and the corresponding market clearing prices $(\lambda_{n,t}, \forall n, \forall t)$. On the other hand, based on its scheduled production and its actual production, the investor calculates the production to be bought/sold in the balancing market $(P_{n,t}^{\mathrm{W,Bal}}(\omega), \forall n, \forall t, \forall \omega)$, for each DA market clearing condition and scenario. Note that the operation of both the DA and the balancing markets under different DA market clearing conditions and scenarios influence the wind power investment decisions.

Note that we distinguish between:

1) Available/maximum wind power production: $k_{n,t}^{\mathrm{W}}(\omega)(X_n^{\mathrm{W},(0)} + X_n^{\mathrm{W}})$. This is an uncertain parameter determined by both the wind power capacity factor $k_{n,t}^{\mathrm{W}}(\omega)$ and the old and newly built wind power capacity.
2) Wind power cleared in the DA market: $P_{n,t}^{\mathrm{W}}$. This is a decision variable pertaining to the DA market. Note that the optimal value of this variable is not an actual value of wind power production. It is rather a contractual value expressing the wind power to be delivered. This is so because the actual wind power production is not known at the time that the DA market is cleared.
3) Wind power production: $P_{n,t}^{\mathrm{W}}$; and power bought from/sold to the balancing market: $P_{n,t}^{\mathrm{W,Bal}}(\omega)$. These decision variables depend on the maximum wind power production explained in item 1) and the wind power cleared in the DA market explained in item 2), in such a way that the wind power production (defined as a nonnegative variable) and the power bought from/sold to the balancing market (which can be either positive and negative) is equal to the wind power cleared in the DA market.

Finally, note that we consider a wind power investor that pursues determining the wind power capacity to be built in an existing electric energy system. Once the wind power investor has built a wind power capacity level, it participates strategically in the DA market, while it also participates as a deviator in the balancing market in which it buys/sells its production deviations. Since the DA market is generally the market with the largest volume of trading, we only explicitly model the clearing of the DA market, while we model the balancing market through a set of scenarios. Nevertheless, note that modeling explicitly the clearing of the balancing market is also possible. In such a case, the resulting model would be a multi-stage complementarity model whose working is sketched below:

1) At a first stage, the wind power investor decides the sizing and siting of the wind power units to be built in the system.
2) At a second stage, the wind power investor decides the production level and the price to be offered to the DA market.
3) At a third stage, based on the clearing of the DA market and knowing with almost certainty its actual production, the wind power investor decides the production to be bought/sold in the balancing market, as well as its offer price curve to this market.

Note that these stages would be linked through non-anticipativity constraints to prevent anticipating information.

III. Model Formulation

A. Notation

The main notation used in this paper is stated below.

Constants:

B_k	Susceptance of line k.
$c_{i,b}^{\mathrm{G}}$	Marginal cost of the bth production block of the ith generation unit.
$c^{\mathrm{W,max}}$	Investment budget for wind power.
$c_n^{\mathrm{W}}/\tilde{c}_n^{\mathrm{W}}$	Investment cost/annualized investment cost of wind power at node n.
$f_l^{\max}$	Transmission capacity of line l.
$k_{n,t}^{\mathrm{W}}(\omega)$	Wind power capacity factor at node n in the tth DA market clearing condition and scenario ω.

N_t^{H} Number of hours comprising the tth DA market clearing condition.

$P_{d,t}^{\mathrm{D}}$ Power consumed by the dth demand in the tth DA market clearing condition.

$P_{i,b}^{\mathrm{G,max}}$ Upper limit of the bth production block of the ith generation unit.

$X_n^{\mathrm{W,max}}$ Maximum wind power capacity that can be built at node n.

$X_n^{\mathrm{W},(0)}$ Wind power capacity previously built at node n.

$\gamma(\omega)$ Weight of scenario ω.

Variables:

$f_{l,t}$ Power flow through line l in the tth DA market clearing condition.

$P_{i,b,t}^{\mathrm{G}}$ Power scheduled to be produced by the bth production block of the ith generation unit in the tth DA market clearing condition.

$P_{n,t}^{\mathrm{W,Bal}}(\omega)$ Power bought/sold by the wind investor in the balancing market at node n in the tth DA market clearing condition and scenario ω.

$P_{n,t}^{\mathrm{W,Of}}$ Wind power offered to the DA market at node n in the tth DA market clearing condition.

$P_{n,t}^{\mathrm{W,P}}(\omega)$ Wind power produced at node n in the tth DA market clearing condition and scenario ω.

$P_{n,t}^{\mathrm{W}}$ Wind power cleared in the DA market at node n in the tth DA market clearing condition.

X_n^{W} Wind power capacity to be built at node n.

$\alpha_{n,t}^{\mathrm{W}}$ Wind power offer price at node n in the tth DA market clearing condition.

$\delta_{n,t}$ Voltage angle at node n in the tth DA market clearing condition.

$\lambda_{n,t}$ LMP at node n in the tth DA market clearing condition.

Indices and Sets:

$r(l)/s(l)$ Receiving-end/sending-end node of line l.

Ω^{G} Set of indices of generation units (other than the wind power units of the strategic investor).

Ω^{L} Set of indices of transmission lines.

Ω^{N} Set of indices of nodes.

Ω^{T} Set of indices of DA market clearing conditions representing the target year.

Ψ_n^{D} Set of indices of demands located at node n.

Ψ_n^{G} Set of indices of generation units (other than the wind power units of the strategic investor) located at node n.

Ψ_t^{ω} Set of indices of scenarios within the tth DA market clearing condition.

Υ_i^{G} Set of indices of production blocks of the ith generation unit.

B. Bilevel Model

The problem of identifying the optimal wind power investment of a strategic wind power investor can be formulated using the bilevel model below:

$$\text{Minimize}_{\Delta^{\mathrm{UL}}\cup\Delta_t^{\mathrm{LL}}} \sum_{n\in\Omega^{\mathrm{N}}} \tilde{c}_n^{\mathrm{W}} X_n^{\mathrm{W}} - \sum_{t\in\Omega^{\mathrm{T}}} N_t^{\mathrm{H}} \left\{ \sum_{n\in\Omega^{\mathrm{N}}} \lambda_{n,t} P_{n,t}^{\mathrm{W}} - \sum_{\omega\in\Psi_t^{\omega}} \gamma(\omega) \left[\sum_{n\in\Omega^{\mathrm{N}}} \lambda_t^{\mathrm{Bal}}(\omega) P_{n,t}^{\mathrm{W,Bal}}(\omega) \right] \right\} \tag{1a}$$

subject to

$$\sum_{n\in\Omega^{\mathrm{N}}} c_n^{\mathrm{W}} X_n^{\mathrm{W}} \le c^{\mathrm{W,max}} \tag{1b}$$

$$0 \le X_n^{\mathrm{W},(0)} + X_n^{\mathrm{W}} \le X_n^{\mathrm{W,max}}, \quad \forall n \tag{1c}$$

$$P_{n,t}^{\mathrm{W,P}}(\omega) + P_{n,t}^{\mathrm{W,Bal}}(\omega) = P_{n,t}^{\mathrm{W}}, \quad \forall n, \forall t, \forall \omega \tag{1d}$$

$$0 \le P_{n,t}^{\mathrm{W,P}}(\omega) \le k_{n,t}^{\mathrm{W}}(\omega) \left(X_n^{\mathrm{W},(0)} + X_n^{\mathrm{W}} \right), \quad \forall n, \forall t, \forall \omega \tag{1e}$$

$$0 \le P_{n,t}^{\mathrm{W,Of}} \le X_n^{\mathrm{W},(0)} + X_n^{\mathrm{W}}, \quad \forall n, \forall t \tag{1f}$$

where $\lambda_{n,t}$ and $P_{n,t}^{\mathrm{W}}, \forall n, \in \arg \Bigg\{$

$$\text{Minimize}_{\Delta_t^{\mathrm{LL}}} \sum_{i\in\Omega^{\mathrm{G}}} \sum_{b\in\Upsilon_i^{\mathrm{G}}} c_{i,b}^{\mathrm{G}} P_{i,b,t}^{\mathrm{G}} + \sum_{n\in\Omega^{\mathrm{N}}} \alpha_{n,t}^{\mathrm{W}} P_{n,t}^{\mathrm{W}} \tag{2a}$$

subject to

$$\sum_{i\in\Psi_n^{\mathrm{G}}} \sum_{b\in\Upsilon_i^{\mathrm{G}}} P_{i,b,t}^{\mathrm{G}} + P_{n,t}^{\mathrm{W}} - \sum_{l\,|\,s(l)=n} f_{l,t} + \sum_{l\,|\,r(l)=n} f_{l,t} = \sum_{d\in\Psi_n^{\mathrm{D}}} P_{d,t}^{\mathrm{D}} : \lambda_{n,t}, \quad \forall n \tag{2b}$$

$$f_{l,t} = B_l \left(\delta_{s(l),t} - \delta_{r(l),t} \right) : \phi_{l,t}, \quad \forall l \tag{2c}$$

$$-f_l^{\max} \le f_{l,t} \le f_l^{\max} : \phi_{l,t}^{\min}, \phi_{l,t}^{\max}, \quad \forall l \tag{2d}$$

$$0 \le P_{i,b,t}^{\mathrm{G}} \le P_{i,b}^{\mathrm{G,max}} : \varphi_{i,b,t}^{\min}, \varphi_{i,b,t}^{\max}, \quad \forall i, \forall b \tag{2e}$$

$$0 \le P_{n,t}^{\mathrm{W}} \le P_{n,t}^{\mathrm{W,Of}} : \varsigma_{n,t}^{\min}, \varsigma_{n,t}^{\max}, \quad \forall n \tag{2f}$$

$$-\pi \le \delta_{n,t} \le \pi : \xi_{n,t}^{\min}, \xi_{n,t}^{\max}, \quad \forall n \setminus n\text{: ref.} \tag{2g}$$

$$\delta_{n,t} = 0 : \chi_{n,t}, \quad n\text{: ref.} \tag{2h}$$

$$\Bigg\}, \forall t.$$

Bilevel model (1)–(2) comprises UL problem (1) and a collection of LL problems (2), one for each DA market clearing condition t. The dual variable corresponding to each constraint of the LL problems is indicated after a colon.

The optimization variables of LL problems are the variables in sets $\Delta_t^{\mathrm{LL}} = \{P_{i,b,t}^{\mathrm{G}}, \forall i, \forall b; P_{n,t}^{\mathrm{W}}, \forall n; f_{l,t}, \forall l; \delta_{n,t}, \forall n; \lambda_{n,t}, \forall n; \phi_{l,t}, \phi_{l,t}^{\min}, \phi_{l,t}^{\max}, \forall l; \varphi_{i,b,t}^{\min}, \varphi_{i,b,t}^{\max}, \forall i, \forall b; \varsigma_{n,t}^{\min}, \varsigma_{n,t}^{\max}, \forall n; \xi_{n,t}^{\min}, \xi_{n,t}^{\max}, \forall n \setminus n\text{: ref.}; \chi_{n,t}^{\min}, n\text{: ref.}\}$, $\forall t$. The optimization variables of the UL problem include the

variables in set Δ_t^{LL} and the additional variables in sets $\Delta^{\mathrm{UL}} = \{X_n^{\mathrm{W}}, \forall n; P_{n,t}^{\mathrm{W,Of}}, \alpha_{n,t}^{\mathrm{W}}, \forall n, \forall t; P_{n,t}^{\mathrm{W,Bal}}(\omega), P_{n,t}^{\mathrm{W,P}}(\omega), \forall n, \forall t, \forall \omega\}$.

The UL problem aims at minimizing the wind power investment cost minus the revenue achieved by participating in both the DA and the balancing markets. The objective function (1a) of the UL problem comprises three terms:

1) Terms $\tilde{c}_n^{\mathrm{W}} X_n^{\mathrm{W}}$ are the annualized investment costs.
2) Terms $\lambda_{n,t} P_{n,t}^{\mathrm{W}}$ are the revenues achieved by the strategic wind investor by participating in the DA market, which are computed as the wind production cleared in this market times the LMP of the corresponding node.
3) Terms $\lambda_t^{\mathrm{Bal}}(\omega) P_{n,t}^{\mathrm{W,Bal}}(\omega)$ are the costs/revenues of buying/selling in the balancing market. These terms depend on the scenarios within each DA market clearing condition and are computed as the balancing market price times the production bought/sold in the balancing market. Each of these terms is multiplied by the weight of the corresponding scenario.

Terms in 2) and 3) are multiplied by factor N_t^{H} to obtain annual expected revenues, comparable with annualized investment costs. For the sake of simplicity, we consider that the production cost of wind power is null.

Constraints of this UL problem include constraint (1b) that imposes a cap on the investment budget; constraints (1c) that impose a limit on the capacity to be built at each node; constraints (1d) stating that the wind production cleared in the DA market must be equal to the wind production plus the production bought/sold in the balancing market for all scenarios (we assume that there is no limit in the production bought/sold in the balancing market); constraints (1e) that limit the wind production to the wind production availability for each node and scenario; and finally constraints (1f) that establish that the wind production level offered to the DA market must be nonnegative, and lower than or equal to the existing plus the newly built wind power capacity at each node.

On the other hand, each LL problem (2) represents the DA market clearing for each DA market clearing condition t. The objective function (2a) aims at maximizing the social welfare. Demands are considered inelastic for the sake of simplicity, i.e., demands are constant and known within each DA market clearing condition t. However, note that modeling demand bids can be easily embedded within the proposed model as in [18]. Producers other than the strategic investor are considered competitive and offer their production at their marginal costs. Note that the offer prices of the strategic investor $(\alpha_{n,t}^{\mathrm{W}}, \forall n, \forall t)$ are decision variables of the UL problem but constants in the LL problems and thus, LL problems are linear. Constraints (2b) represent the power balance at each node of the system. Constraints (2c) define the power flows through lines (using a dc model without losses), limited to the capacity of these lines by inequalities (2d). Constraints (2e) and (2f) impose bounds on the production of generation units (other than the strategic wind units) and strategic wind units, respectively. Finally, constraints (2g) impose limits on voltage angles and constraints (2h) fix to zero the voltage angle at the reference node.

C. MPEC

Given that LL problems (2) are linear, each of these problems can be replaced by its Karush-Kuhn-Tucker (KKT) optimality conditions. These KKTs are included as constraints of the UL problem (1) rendering the MPEC below:

$$\text{Minimize}_{\Delta^{\mathrm{UL}} \cup \Delta_t^{\mathrm{LL}}} \quad (1a) \tag{3a}$$

subject to

$$\text{Constraints (1b)} - \text{(1f)} \tag{3b}$$

$$\left\{ \text{Constraints (2b)} - \text{(2h)} \right. \tag{3c}$$

$$c_{i,b}^{\mathrm{G}} - \lambda_{n(i),t} + \varphi_{i,b,t}^{\max} - \varphi_{i,b,t}^{\min} = 0, \quad \forall i, \forall b \tag{3d}$$

$$\alpha_{n,t}^{\mathrm{W}} - \lambda_{n,t} + \varsigma_{n,t}^{\max} - \varsigma_{n,t}^{\min} = 0, \quad \forall n \tag{3e}$$

$$\lambda_{s(l),t} - \lambda_{r(l),t} - \phi_{l,t} + \phi_{l,t}^{\max} - \phi_{l,t}^{\min} = 0, \quad \forall l \tag{3f}$$

$$\sum_{l \,|\, s(l)=n} B_l \phi_{l,t} - \sum_{l \,|\, r(l)=n} B_l \phi_{l,t} + \xi_{n,t}^{\max} - \xi_{n,t}^{\min} = 0, \quad \forall n \setminus n\text{: ref.} \tag{3g}$$

$$\sum_{l \,|\, s(l)=n} B_l \phi_{l,t} - \sum_{l \,|\, r(l)=n} B_l \phi_{l,t} - \chi_{n,t} = 0, \quad n\text{: ref.} \tag{3h}$$

$$0 \le \phi_{l,t}^{\max} \perp f_l^{\max} - f_{l,t} \ge 0, \quad \forall l \tag{3i}$$

$$0 \le \phi_{l,t}^{\min} \perp f_{l,t} + f_l^{\max} \ge 0, \quad \forall l \tag{3j}$$

$$0 \le \varphi_{i,b,t}^{\max} \perp P_{i,b}^{\mathrm{G,max}} - P_{i,b,t}^{\mathrm{G}} \ge 0, \quad \forall i, \forall b \tag{3k}$$

$$0 \le \varphi_{i,b,t}^{\min} \perp P_{i,b,t}^{\mathrm{G}} \ge 0, \quad \forall i, \forall b \tag{3l}$$

$$0 \le \varsigma_{n,t}^{\max} \perp P_{n,t}^{\mathrm{W,Of}} - P_{n,t}^{\mathrm{W}} \ge 0, \forall n \tag{3m}$$

$$0 \le \varsigma_{n,t}^{\min} \perp P_{n,t}^{\mathrm{W}} \ge 0, \quad \forall n \tag{3n}$$

$$0 \le \xi_{n,t}^{\max} \perp \pi - \delta_{n,t} \ge 0, \quad \forall n \setminus n\text{: ref.} \tag{3o}$$

$$0 \le \xi_{n,t}^{\min} \perp \delta_{n,t} + \pi \ge 0, \quad \forall n \setminus n\text{: ref.} \tag{3p}$$

$$\Bigg\}, \ \forall t.$$

Constraints (3d)–(3p) are the KKT optimality constraints of LL problems (2), while constraints (3i)–(3p) are the so-called complementarity constraints.

MPEC (3) above has two sources of nonlinearities: terms $\lambda_{n,t} P_{n,t}^{\mathrm{W}}$ in the objective function (3a) and the complementarity constraints (3i)–(3p). The nonlinearities in the objective function can be linearized through exact linear expressions based on the strong duality equality as explained in [19]. On the other hand, nonlinearities in the complementarity constraints are linearized using the Fortuny-Amat transformation [20], rendering a MILP problem that can be solved using available branch-and-cut solvers [21].

The number of variables of the proposed model is directly related to both the considered number of scenarios and the number of DA market clearing conditions. This may result in intractable problems if the number of scenarios and the number of DA market clearing conditions are very large. However, note that if the investment decision variables, i.e., $X_n^{\mathrm{W}}, \forall n$, are fixed to

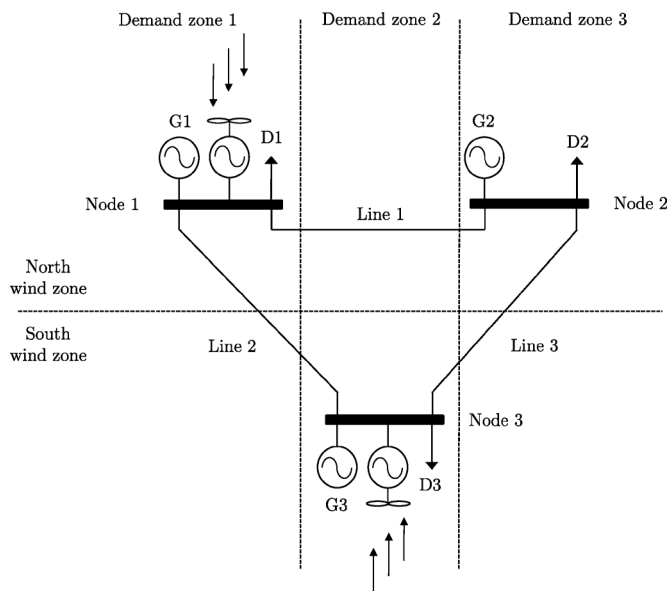

Fig. 5. Three-node system: Network.

TABLE I
THREE-NODE SYSTEM: CONVENTIONAL GENERATION UNIT AND DEMAND DATA

Node #	Generation units		Peak demand (MW)
	Offer size (MW)	Offer price (€/MWh)	
1	40, 40, 30, 30	65, 75, 84, 96	120
2	50, 40, 30, 20	61, 72, 81, 90	100
3	30, 20, 20, 20	63, 80, 86, 98	100

given values, the problem decomposes by DA market clearing condition t. This decomposable structure allows us to use partitioning techniques, e.g., Benders' decomposition, to efficiently tackle this problem [8].

IV. ILLUSTRATIVE EXAMPLE

A. System Data

The proposed model is illustrated using the three-node system depicted in Fig. 5 that comprises three nodes, three conventional generation units (G1, G2, and G3), three demands, and three transmission lines. Data defining conventional generation units and demands are given in Table I. Regarding branch data, all lines have a susceptance equal to 5 p.u. and a capacity of 100 MW.

A wind power capacity of 100 MW installed at node 3 is owned by the wind power investor. New wind units can be built at nodes 1 and 3 up to 300 MW at each node (considering both the old and newly built units). Investment cost at all nodes is considered equal to €1 000 000 per MW being the annualized investment cost equal to €100 000 per MW. Investment budget is limited to €3500 million.

B. Demand, Wind Power Production and Balancing Market Price Data

Demand data is obtained from hourly historical data of aggregated demand in the Iberian Peninsula throughout year 2008 [15]. The three-node system provided in Fig. 5 comprises three demands zones: 1, 2, and 3. The demand in zones 1 and 2 is assumed to be the same as in zone 3 with 2 and 1 hours lags, respectively. This assumption is made to obtain disaggregated demand data.

TABLE II
DEMAND FACTOR CLUSTERS DATA

t	$k^{\mathrm{D}}_{\mathrm{Zone\ 1}}$ (pu)	$k^{\mathrm{D}}_{\mathrm{Zone\ 2}}$ (pu)	$k^{\mathrm{D}}_{\mathrm{Zone\ 3}}$ (pu)	Weight (h)
1	0.7530	0.7570	0.7539	1333
2	0.6037	0.6036	0.6124	147
3	0.8112	0.8189	0.8188	409
4	0.8132	0.8157	0.8100	563
5	0.8393	0.8437	0.8388	385
6	0.8375	0.8458	0.8418	310
7	0.7883	0.7943	0.7909	115
8	0.6430	0.6417	0.6471	159
9	0.6501	0.6431	0.6449	349
10	0.6529	0.6474	0.6474	695
11	0.6250	0.6249	0.6314	516
12	0.5986	0.5930	0.5977	1243
13	0.7484	0.7488	0.7479	91
14	0.7427	0.7417	0.7423	169
15	0.8251	0.8274	0.8217	296
16	0.8709	0.8754	0.8700	519
17	0.6255	0.6230	0.6271	474
18	0.6559	0.6529	0.6562	400
19	0.6649	0.6602	0.6631	480
20	0.8383	0.8447	0.8366	107

On the other hand, we consider that this system comprises two wind zones: North (nodes 1 and 2) and south (node 3). Wind speed data in the north and south zones are obtained from historical hourly data throughout year 2008 in the towns of Tortosa and Tarifa (northeast and southwest Spain, respectively). Wind conditions are comparatively better in the south than in the north zone. These wind speeds are obtained using the databases developed by University of Cantabria [22]. Wind speeds are then transformed into wind capacity factors using the wind-speed/wind-power production curve of a Nordex N80/2500 turbine [23].

Using these historical data and following the procedure described in Section II-B, we obtain 20 clusters, whose data is provided in Table II. Each cluster represents a DA market clearing condition. Demand factors $(K^{\mathrm{D}}_{\mathrm{Zone}i}, \forall\, i)$ multiplied by the corresponding peak demand give the demand for each DA market clearing condition t.

The 20 clusters provided in Table II constitute different DA market clearing conditions. Within each of these conditions, we consider a set of 10 wind production and balancing market price scenarios following the procedure described in Section II-B.

C. Results

The optimal investment decisions consist of building 150 and 200 MW of wind capacity at nodes 1 and 3, respectively. The investment budget of €3500 million limits the wind capacity to be built throughout the system to 350 MW (investment costs are equal across nodes). The investor decides to built all available capacity at node 3 where it already owns 100 MW. Such node

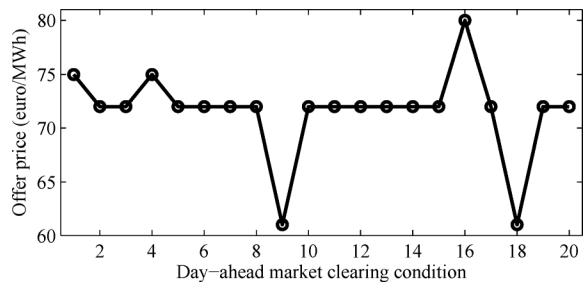

Fig. 6. Three-node system results: Offer prices.

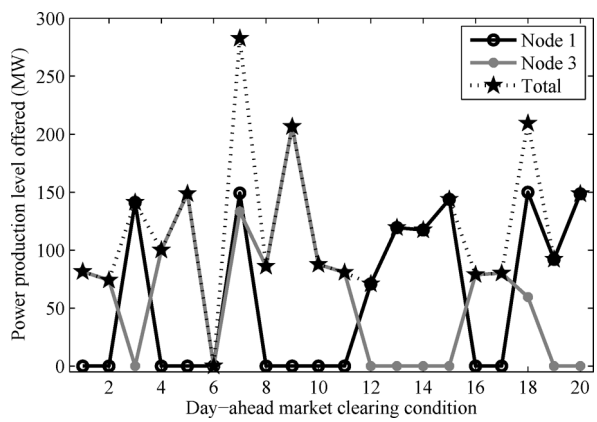

Fig. 7. Three-node system results: Production levels offered.

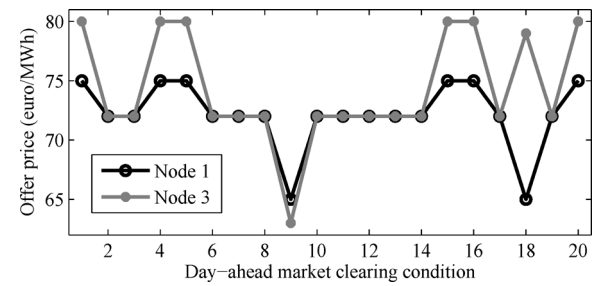

Fig. 8. Three-node system results: Offer prices for the congested network case.

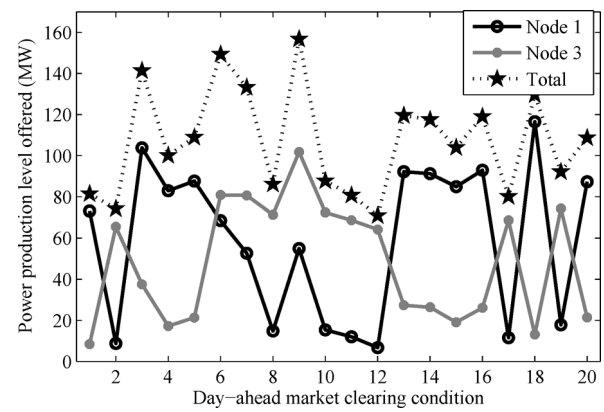

Fig. 9. Three-node system results: Production levels offered for the congested network case.

has comparatively better wind conditions than node 1. However, it also builds 150 MW at node 1 to complete the 350 MW that can be built.

Once the newly built capacity is ready to operate, the wind investor participates and behaves strategically in the DA market. Fig. 6 depicts the offer price for each DA market clearing condition t. The investor exercises market power and offers prices equal to the resulting LMPs, i.e., it fixes the market prices. The network has enough transmission capacity and no transmission congestion occurs in any case. Thus, LMPs and offer prices are equal across nodes.

Fig. 7 depicts the production level offered at each node and for each DA market clearing condition t. Note that since no transmission congestion occurs in this case, it is immaterial at which node the production is offered since the investor owns the wind units built at both nodes, 1 and 3, and thus, it can combine the productions in both locations. This is the reason that explains that in most of the DA market clearing conditions, the production level offered at one of these nodes is null.

Prices and production levels offered to the DA market are different for different DA market clearing conditions. These differences depend on the demand conditions, as well as on the wind power production and balancing market price scenarios associated to each DA market clearing condition. For example, in those DA market clearing conditions whose associated balancing market prices are comparatively low, the wind power investor generally offers a high production level to the DA market and buys, if needed, the difference among its scheduled and actual production in the balancing market. On the other hand, if the associated balancing market prices are comparatively high, the wind power investor offers a comparatively low production level to the DA market. This way, on one hand the wind power investor reduces the risk of having to buy in the balancing market at a comparatively high price, and on the other hand, the wind power investor can sell in the balancing market in the case that its actual production is higher than its scheduled level, being paid at a comparatively high price.

Next, to analyze the effect of transmission congestion we consider that the capacity of the transmission lines connecting the north and south zones is limited to 20 MW. The optimal investment decisions in this case match the investment decisions of the uncongested case, i.e., the investor builds 150 and 200 MW of wind capacity at nodes 1 and 3, respectively. However, as a result of transmission congestion, the offering strategy of the wind power investor significantly changes as described below.

Fig. 8 depicts the offer price for each DA market clearing condition t. As in the uncongested case, the optimal solution results in that offer prices are equal to the resulting LMPs. However, in this case LMPs are different at different nodes as a consequence of transmission congestion.

On the other hand, Fig. 9 depicts the production level offered at each node and for each DA market clearing condition t. As transmission capacity is limited in this case and LMPs are different at different nodes, the wind investor cannot combine the production of wind units of nodes 1 and 3 as it does in the uncongested case.

Finally, we analyze the gain of adopting a strategic position. To do so, we compare the results of solving the strategic wind investment problem with those obtained by a non-strategic investor. We assume that the non-strategic wind investor offers

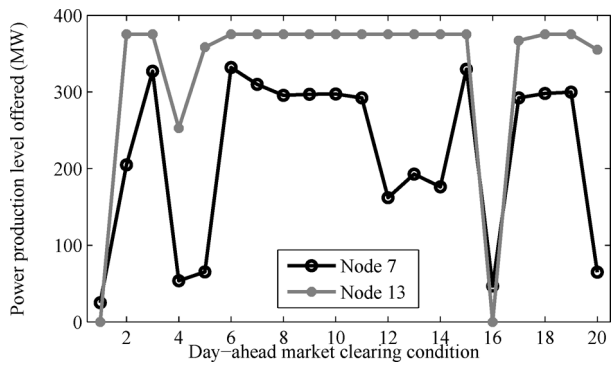

Fig. 10. IEEE 24-node RTS case study results: Production levels offered.

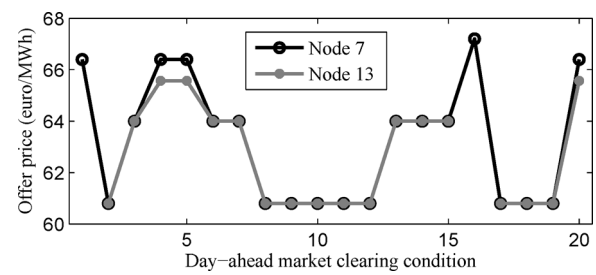

Fig. 11. IEEE 24-node RTS case study results: Offer prices.

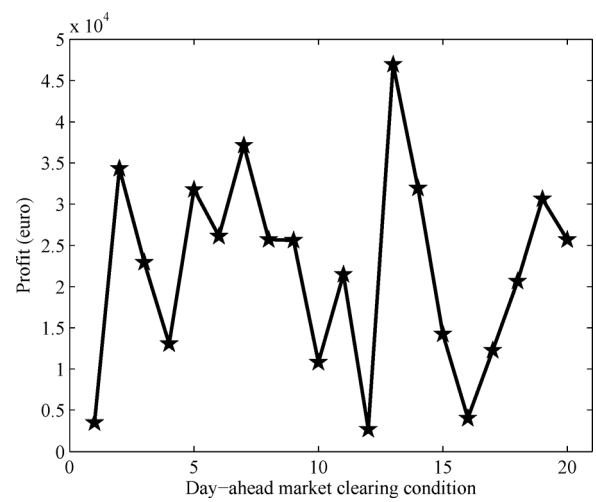

Fig. 12. IEEE 24-node RTS case study: Profits.

its expected production at zero price (which is the typical situation in most electricity markets). Results show that by adopting a strategic position, the investor increases its profit 30.85% and 71.72% for the uncongested and congested cases, respectively.

V. Case Studies

The proposed model is further analyzed using the IEEE 24-node RTS and the IEEE 118-node TS. Data defining these systems can be found in [24] and [25], respectively.

A. IEEE 24-Node RTS

The IEEE 24-node RTS is considered to be divided in three demand zones and two wind zones (north and south) as described in [17]. Data defining demands, wind productions and balancing market prices in different DA market clearing conditions and balancing market scenarios are considered to be the same than those considered in Section IV-B.

Wind units can be built at nodes 7 and 13 up to 500 MW at each node. The investor previously owns wind units of 100 and 200 MW at nodes 7 and 13, respectively. Investment costs are considered equal to those provided in the illustrative example, being the annualized investment cost equal to 11.68% of the total cost. The investment budget is considered unlimited.

The optimal solution consists of building 400 and 175.3 MW of wind capacity at nodes 7 and 13, respectively. Considering both this newly built capacity and the old units result in that the wind power investor owns 500 and 375.3 MW of wind power capacity at nodes 7 and 13, respectively. The investment budget is considered unlimited in this case study; however, the optimal investment only considers building 175.3 MW of new capacity at node 13. This node is located in the North wind zone (i.e., it has worse wind conditions than node 7) and, despite the fact that the wind investor exercises market power and fixes LMPs, building additional capacity at this node would decrease LMPs to a non-profitable level for the investor.

The optimal power production level and prices offered to the DA market for each DA market clearing condition are depicted in Figs. 10 and 11, respectively. The wind investor exercises market power and fixes the market clearing prices. Some lines become congested in some DA market clearing conditions. This explains the differences among LMPs of nodes 7 and 13 for some of these conditions. On the other hand, the differences in the production offers in terms of both power and price at different nodes and for different DA market clearing conditions depend on three issues: the wind production availability, the demands, and the balancing market prices. Based on these three parameters, the wind power investor adapts its offering strategy in the DA market. Based on the demand conditions and the offers of other market participants, the wind power investor mainly determines the offer price. For example, note that in the DA market clearing conditions 2, 8–12, and 17–19, the demand is comparatively low (see Table II) and the offer prices are also comparatively low. Regarding offered production levels, the wind power investor offers comparatively high production levels for these DA market clearing conditions with associated comparatively low balancing market prices.

Additional results are provided in Fig. 12 that depicts the total profit achieved by the wind investor for each DA market clearing condition. This total profit comprises the profit achieved in both the DA and in the balancing markets. Note that this profit is the expected profit through scenarios within each DA market clearing condition. For some of these conditions, the profit achieved in the balancing market is positive which means that the investor sells (in average values) part of its production in the balancing market, while this profit is negative in some other DA market clearing conditions; in these cases, the investors buys (in average values) its deficit of production in the balancing market paying at the corresponding balancing market price of each scenario.

Finally, we compare the optimal investment decisions of a strategic wind investor and a non-strategic one. The optimal investment decisions of a non-strategic investor consists of

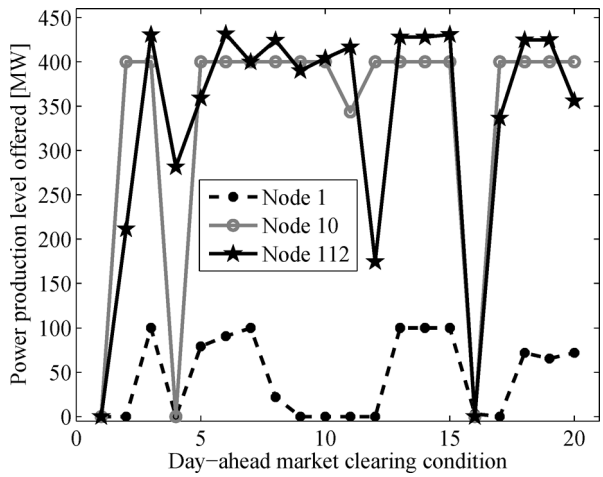

Fig. 13. IEEE 118-node TS case study results: Production levels offered.

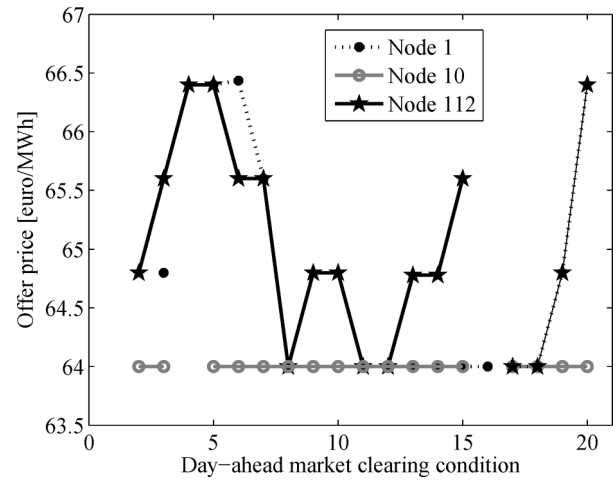

Fig. 14. IEEE 118-node TS case study results: Offer prices.

building 222.7 and 0 MW at nodes 7 and 13, respectively. Note that these investment decisions are quite different to those adopted considering a strategic position. Additionally, by adopting a strategic behavior, i.e., deciding both the production level and offer price to the DA market, the wind investor obtains an expected profit that is 26.43% higher than that achieved by a non-strategic investor.

B. IEEE 118-Node TS

In order to further analyze the proposed strategic wind power investment model, we solve model (3) for the IEEE 118-node TS. We consider that this system is divided in two demand zones and two wind zones, south and north. Data defining demands, wind productions, and balancing market prices in different DA market clearing conditions and balancing market scenarios are considered to be the same than those considered in Section IV-B.

Wind units can be built at nodes 1, 10, and 112, up to 800 MW at each node. Nodes 10 and 112 are located in the south wind zone, the zone with the best wind conditions, while node 1 is located in the north wind zone. The investor already owns wind power units of 100, 300 and 200 MW at nodes 1, 10, and 112, respectively. Investment costs are considered equal to those provided in the illustrative example, being the annualized investment cost equal to 11.68% of the total cost. The investment budget is limited to €800 million, equivalent to limiting the wind power capacity to be built to 800 MW.

The optimal investment decisions considering an optimality gap of 0.65% consist of building 200 and 600 MW at nodes 10 and 112, respectively. The strategic wind power investor builds all available wind power capacity (800 MW) at nodes 10 and 112, i.e., at nodes in the south wind zone. It builds no capacity at node 1, located in the north wind zone and with worse wind conditions.

Figs. 13 and 14 depict the optimal power production levels and the prices offered to the DA market for each DA market operating condition, respectively.

The production level offered at each node changes throughout the DA market operating conditions based on the demand levels of each of these conditions, as well as on the wind power production and the balancing market price scenarios. Note that despite no new wind power capacity is built at node 1, the wind power investor already owns 100 MW of wind power capacity at this node and offers production levels different from zero for some DA market operating conditions.

Regarding offer prices, differences occur among different DA market clearing conditions, depending on wind production and demand levels, and among different nodes as a consequence of the congestion in some of the transmission lines. These offer prices match the resulting LMPs at different nodes.

C. Computational Issues

The computation times required to solve the MILP counterpart of MPEC (3) using CPLEX 12.2.0.1 [21] under GAMS [26] on a Linux-based server with four processors clocking at 2.9 GHz and 250 GB of RAM are 0.52 and 2.42 h for the IEEE 24-node RTS and the IEEE 118-node TS case studies, respectively. These times are compatible with an investment planning study such as the one carried out in this paper. However, if the system under study has a larger number of nodes and/or a larger number of DA market clearing conditions and scenarios is considered, the computation time might significantly increase and even make the problem intractable. Nevertheless, note that if investment decisions variables, i.e., $X_n^{\mathrm{W}}, \forall n$, are fixed to given values, MPEC (3) can be decomposed by DA market clearing condition and Benders' decomposition [7] can be applied, reducing the associated computational burden.

VI. Conclusion

We propose a bilevel model to identify the optimal investment expansion of a strategic wind power investor. This investor participates and exercises market power in the DA market, deciding both the production level and price offered. It also participates in the balancing market, in which it buys/sells its production deviations.

Given the structure of the proposed model and the case studies carried out, the conclusions below are in order:

1) Adopting a strategic position influences the wind power investment decisions.

2) The strategic behavior allows the wind power investor to increase its expected profit with respect to a price-taker behavior.
3) The benefits of adopting a strategic position are specially relevant when the system experiences transmission congestion.
4) The proposed model is tractable provided that the number of nodes of the system and the number of scenarios taken into account are moderate. If needed, decomposition techniques can be applied to reduce the computational burden.

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