A Transmission-Cost-Based Model to Estimate the Amount of Market-Integrable Wind Resources

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***Abstract*—In the pursuit of the large-scale integration of wind power production, it is imperative to evaluate plausible frictions among the stochastic nature of wind generation, electricity markets, and the investments in transmission required to accommodate larger amounts of wind. If wind producers are made to share the expenses in transmission derived from their integration, they may see the doors of electricity markets closed for not being competitive enough. This paper presents a model to decide the amount of wind resources that are economically exploitable at a given location from a transmission-cost perspective. This model accounts for the uncertain character of wind by using a modeling framework based on stochastic optimization, simulates market barriers by means of a bi-level structure, and considers the financial risk of investments in transmission through the conditional value-at-risk. The major features of the proposed model, which is efficiently solved using Benders decomposition, are discussed through an illustrative example.**

***Index Terms*—Bilevel programming, economic appraisal, transmission expansion, wind power.**

NOTATION

THE main notation used throughout the paper is stated below for quick reference. Dual variables and other minor symbols are defined as required in the main text.

A. Indices, Numbers, and Sets

$e(\ell)$	Receiving-end bus of line ℓ.
i	Index of conventional generating units, from 1 to $\mathrm{N_G}$.
j	Index of demands, from 1 to $\mathrm{N_D}$.
k	Index of Benders cuts, from 1 to ν (iteration counter).
ℓ	Index of transmission lines, from 1 to $\mathrm{N_L}$.
m	Index of energy blocks offered by generating units, from 1 to $\mathrm{N}_{\mathrm{M}_i}$ (number of energy blocks offered by unit i).
n	Index of system buses, from 1 to $\mathrm{N_B}$.
$s(i)$	Index of the bus where unit i is located.
$s(j)$	Index of the bus where load j is located.
$o(\ell)$	Sending-end bus of line ℓ.
ω	Index of wind power and demand scenarios, from 1 to N_Ω.
y	Index of payback periods, from 1 to $\mathrm{N_Y}$.
Φ_n^{D}	Set of indices of loads located at node n.
Φ_n^{G}	Set of indices of units located at node n.

B. Constants

$b(\ell)$	Susceptance of line ℓ (per unit).
$C_\ell^{\max}$	Maximum capacity of line ℓ ($\ell \geq 2$) (MW).
$p_{iy}^{\max}(m)$	Size of the mth energy block of the supply cost function of unit i in payback period y (MW).
T	Time length of payback periods (h).
V_{jy}	Value of lost load for consumer j in payback period y (\$/MWh).
$\gamma_{iy}(m)$	Marginal cost of the mth energy block of the supply cost function of unit i in payback period y (\$/MWh).
$\pi_{y\omega}$	Probability of occurrence of scenario ω in payback period y.
ϑ_y	Per unit confidence level in payback period y.

C. Functions

$F_y(\cdot)$	Investment cost function for payback period y.

D. Continuous Variables

$C_1^{\max}$	Capacity of the new line to be built (MW).
$D_{jy\omega}^{\mathrm{shed}}$	Load shedding imposed on consumer j in payback period y and scenario ω (MW).
$f_{\ell y\omega}$	Power flow through line ℓ in payback period y and scenario ω (MW).
I_y	Part of the investment cost to be recovered in payback period y (\$).
$p_{iy\omega}(m)$	Power output from the m-th energy block of the supply cost function of unit i in payback period y and scenario ω (MW).

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r_y Line use rate in payback period y (\$/MWh).

$S_{y\omega}$ Wind power spillage in payback period y and scenario ω (MW).

$\delta_{ny\omega}$ Voltage angle at node n in payback period y and scenario ω (rad).

$\eta_{y\omega}, \zeta_y$ Auxiliary variables to compute the CVaR (\$/h).

E. Binary Variables

$v_{iy}(m)$ 0/1 variable to determine the line use rate r_y in payback period y.

F. Random Variables

W Power output from wind resources (MW).

D_{jy} Power consumed by load j in payback period y (MW)

These symbols, when augmented with the subscript ω, represent the realization of the corresponding random variable in scenario ω.

I. Introduction

Wind generation is free of emissions, fast to deploy, and promotes sustainable development. This makes wind generation attractive and justifies the challenging wind penetration goals that most industrialized countries worldwide have set out to achieve [1]–[3]. However, wind power production is variable and highly uncertain, which calls for a next generation of decision support tools to efficiently manage its stochastic nature while safeguarding the security of the energy supply. Further, wind resources are often plentiful in areas far away from the large demand centers [4], [5]. Therefore, a network infrastructure enabling wind farms to evacuate their energy production towards the consumption nodes is a determining factor in the integration of wind, which typically means large investments in transmission expansion and reinforcement. This poses the controversial question "who should pay for such expenses in transmission?".

If wind producers are competitive agents, aiming at maximizing their own benefit in electricity markets, the idea of them being charged for the transmission costs derived from their integration is, at least, worthy of consideration. However, if wind producers are charged too much, they may be consequently expelled from the market for not being competitive enough, thus failing in the worldwide attempt to smoothly integrate wind production into the electricity supply. So we are faced with a problem in which wind power integration, investments in transmission, and market behavior need to be carefully considered.

In this paper, we consider a wind producer that intends to exploit the wind resources available at a given location. In order for these wind resources to be exploited and with the ultimate purpose of increasing the wind power penetration, the system operator is assumed to invest in the transmission expansion or reinforcement required to connect those wind resources to the main grid. Part of such an investment is recovered by the system operator by charging the wind producer for the usage of the new transmission facilities, while, in turn, the wind producer recovers the resulting transmission costs by selling its production in the electricity market at a high enough price.

Since wind power production is uncertain, so is the income generated from the usage of the new transmission facilities. Therefore, the investment in transmission is inherently risky. In this paper, we model the risk-aversion attitude of the system operator via the conditional value-at-risk (CVaR) [6], [7], within a stochastic programming framework [8].

On the other hand, charges for network usage make wind generation more expensive, thus hindering its penetration into electricity markets. We use a bilevel arrangement [9] in which the lower level simulates the market behavior and provides the upper level with the amount of wind generation that is integrated by competitive means. This bilevel structure has been already used in [10] to plan the expansion of the transmission network in such a way that a weighted sum of the investment cost and the expected social welfare over different scenarios is optimized. However, the work developed in [10] does not consider wind production uncertainty. Relevant references on the topic of transmission expansion planning considering wind resources are, for instance, [11], [12], as well as the series of technical reports on the design of a long-term transmission plan for the Electric Reliability Council of Texas (ERCOT) [13]. Nevertheless, in the present paper, we do not tackle the transmission expansion planning problem, at least in a traditional sense. Here, the primary objective is neither to minimize the cost of the transmission investment, nor to maximize the market-based definition of social welfare, but to maximize the integration of wind generation into electricity markets while assessing the financial risk of the required transmission expansion/reinforcement. This way, the proposed model naturally yields an estimate of the *amount of market-integrable wind resources* at a given location and the resulting decision support tool may be very useful to conduct analysis complementary to those available in the technical literature, in which the economic potential of wind resources is appraised (see [15]–[17] and references therein). In these studies, however, crucial factors such as demand and wind uncertainty, load and wind correlation, investments costs and financial risk, market competition or network congestion are either accounted for based on estimates, not explicitly modeled, or just disregarded. Therefore, the main contribution of this paper is to propose a methodology to quantify the amount of competitively exploitable wind resources at a given location accounting for all these factors within a hierarchical optimization framework.

Mathematically, the stochastic bilevel programming model translates into a mixed-integer nonlinear programming problem that is robustly solved using Benders decomposition [14].

The rest of this paper is organized as follows. Section II describes the proposed stochastic bilevel model and its formulation as a mixed-integer nonlinear programming problem. In Section III, the Benders decomposition strategy used to solve it is presented. The major features of the resulting decision support tool are discussed through an illustrative example in Section IV. Lastly, Section V provides some relevant conclusions and proposals for future research.

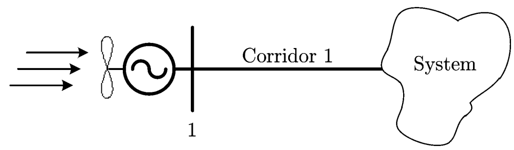

Fig. 1. Schematic representation of the problem.

II. Bilevel Model

A. Problem Statement

Consider the schematic representation in Fig. 1. Assume that, at a certain remote site (node 1 in the figure), there are wind resources that are technically exploitable in the sense defined in [15] (i.e., taking into account factors such as the energy content of the wind, geographical limitations, energy losses in the process of generating electricity, etc.) with a stochastic power output W. For these wind resources to be exploited, a new transmission line (corridor 1 in Fig. 1) connecting the wind site to the power system needs to be built at a cost I. In principle, this cost depends on the line capacity and susceptance, $C_1^{\max}$ and b_1. The system operator plans to pay back the cost of the transmission investment in periodical (e.g., yearly) payments I_y. For this purpose, the system operator charges the wind producer for the use of the new transmission line at a periodical rate of r_y dollars per each megawatt-hour that is transferred through this line. The amount of power flowing through the new line is stochastic and is given by $W - S$, where S is the amount of wind production that is spilled and consequently, not integrated. Therefore, the line use rate r_y constitutes a variable production cost for the wind power producer that directly affects its competitiveness in the electricity market. This way, the primary objective of the system operator is to determine the capacity of the new line $C_1^{\max}$ and the periodical line use rates $r_y, \forall y$, such that the utilization of wind resources is maximized (in expectation given their stochastic nature) while guaranteeing the payback on investment with a given confidence level ϑ_y.

B. Formulation

The mathematical formulation (1)–(2) of the problem stated in Section II-A is based on the following assumptions.

1) The zero marginal production cost of a wind power producer is increased by the use rate of the new transmission line.
2) The cost of the transmission investment is entirely passed on to the wind producer. This statement can be, however, easily relaxed to make consumers share this cost. An implication of this assumption is that the line use rates $\{r_y, \forall y\}$ provided by the proposed model cannot be guaranteed to be optimal (in the sense of maximizing the market integration of wind resources) if a network cost allocation method based on power flow contributions (see, e.g., [18] and [19]) is to be implemented in practice. The consideration of a power-flow-based network cost allocation scheme within the proposed model increases its theoretical complexity and its solution.
3) Loads are inelastic, but uncertain. This assumption is required to keep the model simple in case that loads are made to share the costs of the new transmission facilities.
4) The generation mix of the power system remains unchanged between payback periods.
5) For the sake of mathematical simplicity, the investment in the new transmission line to be built is considered to be solely dependent on its capacity $C_1^{\max}$ (for a given length of the line).
6) The technical potential of wind resources at a given site (as defined in [15], i.e., considering geographical and technical constraints) is assumed to be given and can be described in the form of a stochastic power output W. Thus we do not deal with the wind capacity expansion problem. Notwithstanding this, if several technically feasible wind projects are being considered at a given location, the proposed model can be seen as a valuable tool to assess the economic potential of these projects in terms of transmission investment costs and market competition.
7) The uncertainty associated with the loads and the wind power production can be efficiently modeled through a finite set of scenarios $\{(W_\omega, D_{jy\omega}, \pi_\omega), \omega = 1, \ldots, N_\Omega\}$, where $\{\pi_\omega, \forall\omega\}$ are their associated probabilities of occurrence. This assumption is needed to make the proposed stochastic bilevel model computationally tractable.

The stochastic programming model that results from these assumptions consists of two parts, namely, the upper-level problem (1) and the lower-level problem (2):

$$\underset{\Xi^{\mathrm{UP}}}{\text{Minimize}}\, E[S] = \frac{1}{\mathrm{N_Y}} \sum_{y=1}^{\mathrm{N_Y}} \sum_{\omega=1}^{\mathrm{N_\Omega}} \pi_{y\omega} S_{y\omega} \tag{1a}$$

s. t.

$$\frac{I_y}{T} \leq \zeta_y - \frac{1}{1-\vartheta_y} \sum_{\omega=1}^{\mathrm{N_\Omega}} \pi_{y\omega}\eta_{y\omega}, \quad \forall y \tag{1b}$$

$$\eta_{y\omega} \geq \zeta_y - r_y(W_\omega - S_{y\omega}), \quad \forall y, \forall\omega \tag{1c}$$

$$\eta_{y\omega} \geq 0, \quad \forall y, \forall\omega \tag{1d}$$

$$I_y = F_y(C_1^{\max}), \quad \forall y \tag{1e}$$

$$r_y \geq 0, \quad \forall y \tag{1f}$$

$$C_1^{\max} \geq 0 \tag{1g}$$

$$S_{y\omega} \in \arg\left\{ \underset{\Xi^{\mathrm{LO}}}{\text{Maximize}}\, r_y^* S_{y\omega} - \sum_{i=1}^{\mathrm{N_G}} \sum_{m=1}^{\mathrm{N}_{\mathrm{M}_i}} \gamma_{iy}(m) p_{iy\omega}(m) \right.$$

$$- \sum_{j=1}^{\mathrm{N_D}} V_{jy} D_{jy\omega}^{\mathrm{shed}} \tag{2a}$$

s. t.

$$W_\omega - S_{y\omega} = f_{1y\omega} : \lambda_{1y\omega} \tag{2b}$$

$$\sum_{i\in\Phi_n^{\mathrm{G}}} \sum_{m=1}^{\mathrm{N}_{\mathrm{M}_i}} p_{iy\omega}(m) - \sum_{j\in\Phi_n^{\mathrm{D}}} \left(D_{jy\omega} - D_{jy\omega}^{\mathrm{shed}}\right)$$

$$= \sum_{\ell\,|\,o(\ell)=n} f_{\ell y\omega} - \sum_{\ell\,|\,e(\ell)=n} f_{\ell y\omega} : \lambda_{ny\omega}, \forall n > 1 \tag{2c}$$

$$f_{\ell y\omega} = b_\ell(\delta_{o(\ell)y\omega} - \delta_{e(\ell)y\omega}) : \beta_{\ell y\omega}, \quad \forall\ell \tag{2d}$$

$$f_{\ell y\omega} \leq C_\ell^{\max} : \varepsilon_{\ell y\omega}^{\max}, \quad \forall\ell \tag{2e}$$

$$f_{\ell y\omega} \geq -C_\ell^{\max} : \varepsilon_{\ell y\omega}^{\min}, \quad \forall \ell \tag{2f}$$

$$p_{iy\omega}(m) \leq p_{iy}^{\max}(m) : \alpha_{iy\omega}(m), \quad \forall i, \forall m \tag{2g}$$

$$S_{y\omega} \leq W_\omega : \rho_{y\omega} \tag{2h}$$

$$D_{jy\omega}^{\text{shed}} \leq D_{jy\omega} : \mu_{jy\omega}, \quad \forall j \tag{2i}$$

$$\delta_{ny\omega} \leq \pi : \theta_{ny\omega}^{\max}, \quad \forall n \tag{2j}$$

$$\delta_{ny\omega} \geq -\pi : \theta_{ny\omega}^{\min}, \quad \forall n \tag{2k}$$

$$\delta_{2y\omega} = 0 : \chi_{y\omega} \tag{2l}$$

$$\left. p_{iy\omega}(m) \geq 0, \quad \forall i; S_{y\omega} \geq 0; \quad D_{jy\omega}^{\text{shed}} \geq 0, \quad \forall j \right\}, \quad \forall y, \forall \omega. \tag{2m}$$

In the upper-level problem, the transmission system operator seeks to minimize the amount of exploitable wind resources that is expected to be wasted over the planning horizon, which comprises N_Y payback periods. This is stated by (1a). There are two basic reasons that justify this objective function:

1) The primary aim of model (1)–(2) is to estimate the amount of wind resources at a given location that can be exploited through market competition. To this end, the amount of wind that is curtailed must be minimized in the upper-level problem. Since wind resources are inherently uncertain, the expectation operator is used.
2) The economic expression of "social welfare" that is used in algorithms to clear electricity markets fails to represent the actual social welfare. The integration of wind generation brings benefits that are not accounted for in the market-based definition of "social welfare", e.g., reductions in emissions and fossil-fuel dependence. We start from the premise that this is the reason why many governments worldwide are committed to remarkably increase the share of wind energy in the electricity supply (consider, e.g., the "20-20-20" targets set by the European Union [20]). The research carried out in this paper is thus motivated within the context of a TSO that, following policy guidelines, seeks to facilitate wind integration.

With a view to maximizing wind integration, the system operator must decide the capacity of the new transmission facilities to be built, $C_1^{\max}$, and its use rate, r_y, in each payback period y. Logically, both decision variables are nonnegative, as expressed by (1f) and (1g). The income obtained by the system operator from charging the wind producer for the use of the new transmission facilities is uncertain, being equal to $r_y(W_\omega - S_{y\omega})$ per scenario ω and payback period y. Therefore, the transmission investment is essentially risky and the associated financial risk is limited by ensuring that the CVaR of the income distribution at the confidence level ϑ_y in payback period y is greater than or equal to the corresponding payback payment I_y. This guarantees that the probability of the system operator not being able to comply with its financial duties in payback period y is smaller than $1 - \vartheta_y$. This is linearly formulated by means of the set of equations (1b)–(1d), where T represents the length of the payback periods in hours (e.g., 8760 h for yearly periods). This linear formulation for optimization problems with constraints on risk is presented in [21]. It should be noticed that the risk-aversion attitude of the TSO can be thus controlled by means of the confidence level ϑ_y. Consequently, the proposed model can produce solutions with different degrees of conservatism. This conservatism may reflect the desire of the TSO to be hedged not only against wind and demand uncertainty, but also against modeling errors, such as those pertaining to the uncertainty characterization of wind and demand and/or those just stemming from not considering all the uncertainties involved (e.g., uncertain changes in future generation developments with respect to the envisaged plan). The transmission investment and consequently the payback payments I_y are given as increasing functions F_y of the capacity of the new line to be built ($C_1^{\max}$), as stated by (1e).

Once the capacity $C_1^{\max}$ of the new transmission line and its use rate r_y in each payback period y have been set by the transmission system operator, the new wind power producer is ready to compete in the electricity market, where the amount $S_{y\omega}$ of its production that is not utilized in each scenario ω and payback period y is determined. Therefore, the lower-level problem (2) represents a network-constrained market-clearing procedure and its objective function (2a) consists in maximizing the social welfare accordingly. As the demand is considered to be inelastic, the social welfare boils down to the summation of the term $r_y^* S_{y\omega}$, which results from the wind production costs as explained below, minus the production costs of conventional generators, and minus the costs of involuntary load curtailments. Production costs are computed from the supply cost functions submitted by power producers, which are approximated by energy blocks $p_{iy\omega}(m)$ at marginal costs $\gamma_{iy}(m)$. The wind power producer enters the electricity market with a supply cost function given by the product $r_y^*(W_\omega - S_{y\omega})$, where the superscript "$*$" denotes "optimal value". Therefore, the line use rate r_y^* is a meaningful signal of the competitiveness degree of the wind site under analysis. Since the term $-r_y^* W_\omega$ is constant in the social welfare (from the perspective of the lower-level problem), it can be removed from the objective function (2a). Note that in the case that the wind producer is receiving a production tax credit of $\$t_{y\omega}$/MWh, its supply cost function will be given by $(r_y^* - t_{y\omega})(W_\omega - S_{y\omega})$, where the subscripts y and ω have been added to the tax credit to account for the fact that subsidies schemes are subject to regulatory uncertainty over time. Constraint (2b) constitutes the power balance equation at the wind site (which is considered, without loss of generality, as node 1), while the group of constraints (2c) are the power balance equations at the rest of nodes of the power system. Power flows through all transmission lines are defined by constraints (2d) in keeping with a dc network model. Each power flow is limited in both directions by the corresponding line capacity, as stated by (2e) and (2f). Constraints (2g) define the sizes of the energy blocks with which the supply cost functions of conventional producers are approximated. Note that this approximation is consistent with offering practices in current electricity markets. Constraints (2h) and (2i) are logical bounds according to which the amount of wind power that is spilled and the amount of load that is involuntarily curtailed are smaller than or equal to the actual wind power production and the actual load consumption, respectively. Constraints (2j) and (2k) impose usual limits on the voltage angles at every bus of the system, and constraint (2l) establishes, without loss of generality, node 2 as the reference bus. Lastly, constraints (2m) are variable declarations.

The set $\Xi^{\mathrm{UP}} = \{C_1^{\max}; r_y, I_y, \zeta_y, \eta_{y\omega}, \forall y, \omega\}$ includes all the optimization variables of the upper-level problem, while the set $\Xi^{\mathrm{LO}} = \{S_{y\omega}; p_{iy\omega}(m), \forall i, m; D_{jy\omega}^{\mathrm{shed}}, \forall j, f_{\ell y\omega}, \forall \ell; \delta_{ny\omega}, \forall n\}$ encompasses all the optimization variables of the lower-level problem. Dual variables are provided after the corresponding constraints separated by a colon. For instance, $\lambda_{1y\omega}$ is the dual variable of constraint (2b).

Note that the proposed decision framework provides the maximum amount of wind resources that can be exploited within a market environment considering the required transmission investments. This way, the proposed model may be a useful tool for TSOs to prioritize the exploitation of different wind resource locations, or to identify the most competitive potential wind sites. Likewise, it is important to emphasize the capability of the proposed model to account for multiple factors influencing the market integration of wind resources, namely, transmission costs and allocation scheme, financial risk of the transmission investment, power distribution at the wind site, network topology, power system configuration and uncertainties, changes in the electricity consumption, changes in the generation mix, etc.

Mathematically, the market-clearing procedure (2) is linear and as such, can be replaced by its constraints, the constraints of its dual problem, and the strong duality condition [22]. This way, the bilevel optimization model (1)–(2) can be equivalently transformed into a single-level optimization problem.

It is important to point out that the proposed decision framework can be straightforwardly adapted to consider the problem of a third party investor seeking to maximize its own profit. For this purpose, objective function (1a), which consists in the minimization of the expected wind curtailment, just needs to be replaced with the maximization of the third party's expected profit. Likewise, model (1)–(2) can be also easily generalized to account for different wind projects that simultaneously request for connection at different locations, logically at the cost of higher complexity. This way, analysis of the impact of simultaneous different wind farm connections on their competitiveness can be performed.

C. Dual Problem

The dual problem corresponding to the lower-level problem (2) for year y and scenario ω is the following:

$$\underset{\Xi^{\mathrm{D}}}{\text{Minimize}} \quad \lambda_{1y\omega} W_\omega - \sum_{n=2}^{\mathrm{N_B}} \lambda_{ny\omega} \left(\sum_{j \in \Phi_n^{\mathrm{D}}} D_{jy\omega} \right) + \sum_{\ell=1}^{\mathrm{N_L}} C_\ell^{\max} \left(\varepsilon_{\ell y\omega}^{\max} + \varepsilon_{\ell y\omega}^{\min} \right) + \sum_{i=1}^{\mathrm{N_G}} \sum_{m=1}^{\mathrm{N_{M_i}}} p_{iy\omega}^{\max}(m) \alpha_{iy\omega}(m) + \rho_{y\omega} W_\omega + \sum_{j=1}^{\mathrm{N_D}} D_{jy\omega} \mu_{jy\omega} + \pi \sum_{n=1}^{\mathrm{N_B}} \left(\theta_{ny\omega}^{\max} + \theta_{ny\omega}^{\min} \right) \quad (3a)$$

s. t.

$$\lambda_{1y\omega} + \rho_{y\omega} \geq r_y^* : S_{y\omega} \quad (3b)$$

$$-\lambda_{s(i)y\omega} + \alpha_{iy\omega}(m) \geq -\gamma_{iy}(m) : p_{iy\omega}(m), \quad \forall i, \forall m \quad (3c)$$

$$-\lambda_{s(j)y\omega} + \mu_{jy\omega} \geq -V_{jy} : D_{jy\omega}^{\mathrm{shed}}, \quad \forall j \quad (3d)$$

$$\lambda_{o(\ell)y\omega} - \lambda_{e(\ell)y\omega} + \beta_{\ell y\omega} + \varepsilon_{\ell y\omega}^{\max} - \varepsilon_{\ell y\omega}^{\min} = 0 : f_{\ell y\omega}, \quad \forall \ell \quad (3e)$$

$$-\sum_{\ell \mid o(\ell)=n} b_\ell \beta_{\ell y\omega} + \sum_{\ell \mid e(\ell)=n} b_\ell \beta_{\ell y\omega} + \theta_{ny\omega}^{\max} - \theta_{ny\omega}^{\min} = 0 : \delta_{ny\omega}, \quad \forall n \neq 2 \quad (3f)$$

$$-\sum_{\ell \mid o(\ell)=2} b_\ell \beta_{\ell y\omega} + \sum_{\ell \mid e(\ell)=2} b_\ell \beta_{\ell y\omega} + \theta_{2y\omega}^{\max} - \theta_{2y\omega}^{\min} + \chi_{y\omega} = 0 : \delta_{2y\omega} \quad (3g)$$

$$\varepsilon_{\ell y\omega}^{\max}, \varepsilon_{\ell y\omega}^{\min}, \alpha_{iy\omega}(m), \rho_{y\omega}, \mu_{jy\omega}, \theta_{ny\omega}^{\max}, \theta_{ny\omega}^{\min} \geq 0, \quad \forall i, j, n, \ell, m \quad (3h)$$

where $\Xi^{\mathrm{D}} = \{\varepsilon_{\ell y\omega}^{\max}, \varepsilon_{\ell y\omega}^{\min}, \forall \ell; \alpha_{iy\omega}(m), \forall i; \rho_{y\omega}; \mu_{jy\omega}, \forall j; \lambda_{ny\omega}, \theta_{ny\omega}^{\max}, \theta_{ny\omega}^{\min}, \forall n\}$ is the set of dual variables and $s(i)$ and $s(j)$ are the indexes of buses where generating unit i and load j are located, respectively.

Note that primal variables are indicated after the corresponding set of dual constraints separated by a colon.

D. Equivalent Single-Level Optimization Problem

The strong duality condition states that feasible solutions to the primal and dual problems are indeed primal and dual optimal, respectively, if and only if

$$r_y S_{y\omega} - \sum_{i=1}^{\mathrm{N_G}} \sum_{m=1}^{\mathrm{N_{M_i}}} \gamma_{iy}(m) p_{iy\omega}(m) - \sum_{j=1}^{\mathrm{N_D}} V_{jy} D_{jy\omega}^{\mathrm{shed}} = \lambda_{1y\omega} W_\omega - \sum_{n=2}^{\mathrm{N_B}} \lambda_{ny\omega} \left(\sum_{j \in \Phi_n^{\mathrm{D}}} D_{jy\omega} \right) + \sum_{\ell=1}^{\mathrm{N_L}} C_\ell^{\max} \left(\varepsilon_{\ell y\omega}^{\max} + \varepsilon_{\ell y\omega}^{\min} \right) + \sum_{i=1}^{\mathrm{N_G}} \sum_{m=1}^{\mathrm{M_{N_i}}} p_{iy}^{\max}(m) \alpha_{iy\omega}(m) + \rho_{y\omega} W_\omega + \sum_{j=1}^{\mathrm{N_D}} D_{jy\omega} \mu_{jy\omega} + \pi \sum_{n=1}^{\mathrm{N_B}} \left(\theta_{ny\omega}^{\max} + \theta_{ny\omega}^{\min} \right). \quad (4)$$

This way, the single-level optimization model equivalent to the bilevel problem (1)–(2) results from minimizing the objective function of the upper-level problem subject to the constraints of the upper-level problem, the primal and dual constraints of each lower-level problem (per payback period y and scenario ω), and the strong duality condition for each lower-level problem, that is

$$\underset{\Xi}{\text{Minimize}} \quad (1a) \quad (5a)$$

s. t.

$$(1b)\text{–}(1g) \quad (5b)$$

$$(2b)\text{–}(2m), \forall y, \forall \omega \quad (5c)$$

$$(3b)\text{–}(3h), \forall y, \forall \omega \quad (5d)$$

$$(4), \forall y, \forall \omega \quad (5e)$$

where $\Xi = \Xi^{\mathrm{UP}} \cup \Xi^{\mathrm{LO}} \cup \Xi^{\mathrm{D}}$.

Note that the bilevel arrangement (1)–(2) represents a two-player Stackelberg game between a leader and a follower [23]. The equivalent single-level optimization problem (5) results in the so-called optimistic (strong) Stackelberg game solution. Since the upper-level objective function is the minimization of the expected wind spillage, given equal marginal production costs, wind production is given priority to be dispatched over conventional generation.

The single-level optimization model (5) is a nonlinear programming problem due to products $r_y S_{y\omega}$ and $C_\ell^{\max}(\varepsilon_{\ell y\omega}^{\max} + \varepsilon_{\ell y\omega}^{\min})$, which appear in constraints (1c) and (4). Moreover, as shown in the illustrative example of Section IV, problem (5) is nonconvex with respect to the line use rates $r_y, \forall y$. However, such nonconvexity can be circumvented if we look closely at the physics of the problem. Observe that the wind power producer enters the electricity auction in payback period y with a marginal cost equal to r_y. Consequently, the line use rate r_y represents the cost of the energy block that the wind power production displaces from the electricity supply. Therefore, by appealing to pure economic reasons, the global optimum of problem (5) is reached for a value of r_y equal to one of the energy offer costs $\gamma_{iy}(m)$, i.e., $r_y = \sum_{i=1}^{N_\mathrm{G}} \sum_{m=1}^{N_{\mathrm{M}_i}} v_{iy}(m)\gamma_{iy}(m), \forall y$, where $v_{iy}(m) \in \{0,1\}, \forall(i,m,y)$, are binary variables that must satisfy the logical condition

$$\sum_{i=1}^{\mathrm{N_G}} \sum_{m=1}^{\mathrm{N}_{\mathrm{M}_i}} v_{iy}(m) \leq 1, \quad \forall y. \tag{6}$$

This way, $r_y S_{y\omega} = \sum_{i=1}^{N_\mathrm{G}} \sum_{m=1}^{N_{\mathrm{M_i}}} S_{y\omega} v_{iy}(m)\gamma_{iy}(m)$ and consequently, problem (5) turns into a mixed-integer nonlinear programming problem that can be robustly solved using Benders decomposition, as described in the following section.

III. Solution Procedure: Benders Decomposition

By using Benders decomposition [14], problem (5) is decomposed into a *master* mixed-integer programming problem and N_Y linear programming *subproblems* that are iteratively solved. The master problem is as follows:

$$\underset{z; C_1^{\max}; v_{iy}(m),\ \forall i,y,m}{\text{Minimize}} \quad z \tag{7a}$$

s. t.

$$\begin{aligned} z \geq{}& \frac{1}{\mathrm{N_Y}} \sum_{y=1}^{\mathrm{N_Y}} \sum_{\omega=1}^{\mathrm{N_\Omega}} \pi_{y\omega} S_{y\omega}^{(k)} \\ &+ M \sum_{y=1}^{\mathrm{N_Y}} h_y^{(k)} + \left(\sum_y \epsilon_y^{(k)}\right)\left(C_1^{\max} - C_1^{\max,(k)}\right) \\ &+ \sum_{i=1}^{\mathrm{N_G}} \sum_{y=1}^{\mathrm{N_Y}} \sum_{m=1}^{\mathrm{N}_{\mathrm{M}_i}} \sigma_{iy}^{(k)}(m)(v_{iy}(m) - v_{iy}^{(k)}(m)), \\ &\forall k = 1,\ldots,\nu-1 \end{aligned} \tag{7b}$$

$$\sum_{i=1}^{N_\mathrm{G}} \sum_{m=1}^{N_{\mathrm{M_i}}} v_{iy}(m) \leq 1, \quad \forall y \tag{7c}$$

$$z, C_1^{\max} \geq 0 \tag{7d}$$

$$v_{iy}(m) \in \{0,1\}, \quad \forall i, \forall y, \forall m \tag{7e}$$

where ν is the iteration counter and M is a large enough constant.

In each iteration, a new Benders cut (7b) is added to the master problem, thus restricting the search space. The values of $C_1^{\max}$ and $v_{iy}(m)$ that are obtained from the master problem are then passed to the subproblems. The subproblem for payback period y is formulated as follows:

$$\underset{S_{y\omega}, p_{iy\omega}(m), D_{jy\omega}^{\mathrm{shed}}, f_{\ell y\omega}, \delta_{ny\omega}}{\text{Minimize}} \quad \frac{1}{\mathrm{N_Y}} \sum_{\omega=1}^{\mathrm{N_\Omega}} \pi_{y\omega} S_{y\omega} + M h_y \tag{8a}$$

s. t.

$$\frac{I_y}{T} - h_y \leq \zeta_y - \frac{1}{1-\vartheta_y} \sum_{\omega=1}^{\mathrm{N_\Omega}} \pi_{y\omega} \eta_{y\omega} \tag{8b}$$

$$\text{(1c)–(1e)} \tag{8c}$$

$$\text{(2b)–(2m)}, \quad \forall \omega \tag{8d}$$

$$\text{(3b)–(3h)}, \quad \forall \omega \tag{8e}$$

$$\text{(4)}, \quad \forall \omega \tag{8f}$$

$$h_y \geq 0 \tag{8g}$$

$$v_{iy}(m) = v_{iy}^{(\nu)}(m) : \sigma_{iy}^{(\nu)}(m) \tag{8h}$$

$$C_1^{\max} = C_1^{\max,(\nu)} : \epsilon_y^{(\nu)} \tag{8i}$$

where h_y is a slack variable to avoid subproblem infeasibility.

Observe that, since variables $C_1^{\max,(\nu)}$ and $v_{iy}(m)$, $\forall(i,y,m)$, are fixed by constraints (8h) and (8i), the subproblems are essentially linear programming problems. The Lagrange multipliers $\sigma_{iy}^{(\nu)}(m)$ and $\epsilon_y^{(\nu)}$ associated with these constraints are subsequently used in the master problem to generate a new Benders cut (7b).

IV. Illustrative Example

In this section, we illustrate the major features of the proposed decision-making tool while gaining a grasp of the main factors determining the amount of wind resources at a given location that can be integrated into a power system from a market perspective. To this end, we firstly define a base case consisting of the two-node system depicted in Fig. 2. This small-scale power system includes a load and a conventional power plant at bus 2. Far away from this node, there exists an area (bus 1) where wind resources are plentiful. In order for these resources to be exploited, transmission line 1 needs to be built. Following the guidelines provided in [24] on standard costs of long transmission lines, the cost I of line 1 is assumed to be given as a linear function of its capacity, specifically $I = 100 \cdot 10^3 C_1^{\max}$ (\$). Its reactance is equal to 0.13 p.u. The system operator is committed to paying back the cost of such an investment in one year. Appealing to the illustrative and clarifying nature of this example, we assume that technical and statistical studies state that the power distribution exploitable at site 1 and the electricity consumption of the load at node 2 can be jointly modeled by means of the nine scenarios provided in Table I. The value of lost load is \$1000/MWh. The supply cost function of the conventional generating unit at bus 2 can be described by a piecewise linear approximation made up of eight energy blocks. Table II lists the

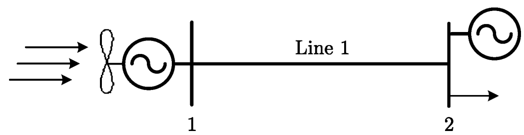

Fig. 2. Two-bus power system.

TABLE I
SCENARIOS FOR WIND PRODUCTION AND DEMAND

Scenario #	Wind power level	Demand level	Probability (Base case)	Probability (Variant)
1	700	1200	0.10	0.20
2	700	800	0.05	0.10
3	700	200	0.20	0.05
4	500	1200	0.15	0.15
5	500	800	0.15	0.20
6	500	200	0.15	0.10
7	200	1200	0.10	0.00
8	200	800	0.05	0.05
9	200	200	0.05	0.15
Correlation			-0.23	0.52

TABLE II
PIECEWISE LINEAR SUPPLY COST FUNCTION OF THE CONVENTIONAL POWER PLANT

Block #	1	2	3	4	5	6	7	8
Size (MW)	50	100	150	50	250	250	300	250
Slope ($/MWh)	0	3	7	12	20	30	45	60

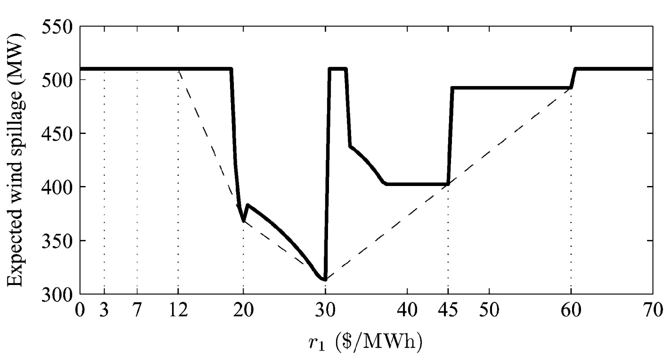

Fig. 3. Objective function (1a) (expected wind spillage in MW) as a function of the line use rate r_1 ($/MWh).

size of each one of these blocks and their corresponding marginal costs.

Unless stated otherwise below, the system operator is supposed to be risk neutral. Mathematically, this translates into solving problem (1)–(2) considering the CVaR of the income distribution for a confidence level equal to 0. In other words, constraint (1b) boils down to enforcing the expected value of the incomes, obtained from charging the wind producer for the use of the new line, to be greater than or equal to the investment cost I.

Fig. 3 shows the wind power production that is expected to be spilled as a function of the line use rate r_1. The plot in this figure is obtained by solving problem (5) while the line use rate r_1 is fixed to the different values shown on the x-axis. As can be seen, the resulting function is far from being convex. It has two strict local optima, being the one located at $r_1 = \$30$/MWh the global optimum. Observe that, for all the values of the line use rate r_1 equal to the marginal costs of the energy blocks in Table II, a local minimum is reached. Intuitively, note that if these local minima are connected, the resulting *envelope* (the dashed line in Fig. 3), which embraces the global minimum, is clearly smoother than the original function and hence can be efficiently reconstructed by the Benders decompostion technique. For this reason, the mixed-integer formulation of problem (1)–(2), based on the introduction of binary variables $v_{iy}(m)$, $\forall(i, y, m)$, makes its solution much easier and more robust.

TABLE III
WIND POWER PRODUCTION AND CONVENTIONAL GENERATION PER SCENARIO-BASE CASE. POWERS IN MW

Scenario #	Integrated wind power	Curtailed wind power	Conventional production
1	516.9	183.1	683.1
2	200	500	600
3	0	700	200
4	500	0	700
5	200	300	600
6	0	500	200
7	200	0	1000
8	200	0	600
9	0	200	200

For the base case described above, the solution to problem (1)–(2) corresponds to $r_1 = \$30$/MWh and $C_1^{\max} = 516.9$ MW, i.e., the amount of wind resources at bus 1 that are expected to be integrated in the electricity market is $\sum_{\omega=1}^{9} \pi_\omega (W_\omega - S_\omega) =$ 196.7 MW, being 313.3 MW the quantity of power production that is expected to be wasted. Table III provides the integrated and curtailed wind generation and the conventional power production per scenario. Observe that the capacity of the new line to be built is fully used only in scenario 1, in which the highest load value coincides with the highest wind power production. Note that if the capacity of the new line was increased beyond its optimal value (516.9 MW), the increment in the line use rate r_1 needed to compensate for the consequent increase in the transmission investment costs would cause part of the wind power production to be displaced by the sixth energy block of the conventional generator (see Table II). Therefore, an increase in the capacity of the new line above 516.9 MW is not economically justified and would be indeed detrimental to the market integration of the wind resources.

In the following, we will compare the solution to the base case with others obtained from different variants to highlight the most relevant aspects of the problem dealt with in this paper.

A. Probability Distribution of Wind Power and Demand

Statistical dependencies between uncertainty sources affecting the operations and planning of a power system, such as

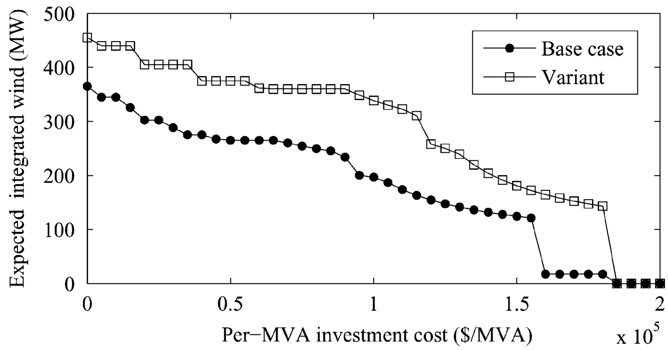

Fig. 4. Expected amount of market-integrable wind resources as a function of the per-MVA transmission cost.

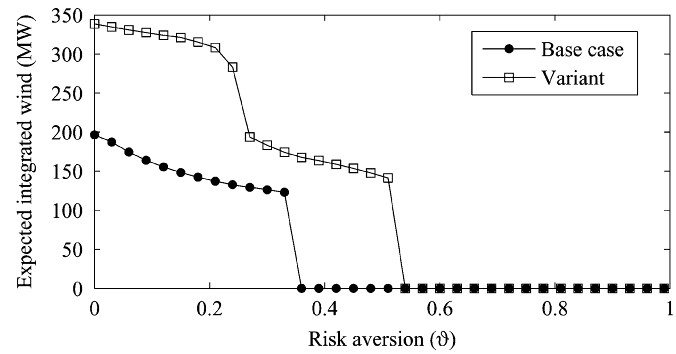

Fig. 5. Expected amount of market-integrable wind resources as a function of the risk-aversion level of the system operator.

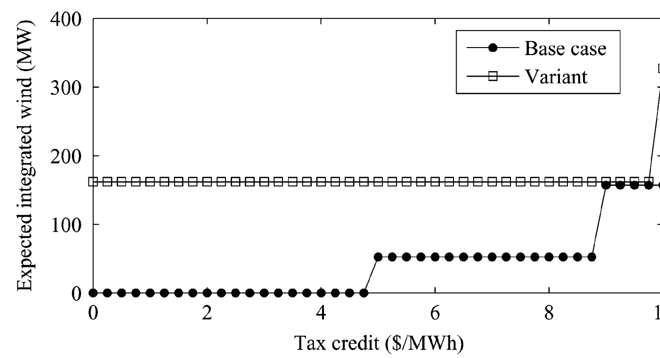

Fig. 6. Expected amount of market-integrable wind resources as a function of the production tax credit received by the wind producer.

the power produced by wind farms and the power consumed by loads, may have a significant effect on the reliability and security of the power system [26]–[28] or on electricity prices [25], [29]. In this section, we exemplify how the correlation between wind production and system demand may also have an impact on the amount of market-integrable wind resources. To this end, we change the probabilities associated with the nine scenarios listed in Table I, thus obtaining a modified case study referred to as "variant". Note that the correlation coefficient between demand and wind power production in the base case is equal to -0.23, whereas it is 0.52 in the variant. We should point out that these two fairly extreme cases have been considered just for illustrative purposes. The results reported in the subsequent sections illustrate the impact of such a correlation.

B. Cost of the Transmission Investment

Considering that the cost of the transmission investment is given by $I = a \cdot C_1^{\max}$, Fig. 4 represents the amount of wind resources that are expected to be integrated in the electricity market as a function of a, i.e., as a function of the transmission cost per installed MVA. One of the main factors influencing the value of a is the length of the transmission line to be built. Thus, larger values of a could well correspond to wind resources further away from the transmission network. As expected, the amount of market-integrable wind resources decreases as the transmission facilities required for them to be exploited become more costly. Notwithstanding this, observe that, for any value of a, the amount of economically exploitable wind resources in the variant is always greater than or at least equal to that in the base case. This is in keeping with the well-known fact that positively correlated wind generation and electricity demand facilitates wind penetration.

C. Risk Aversion of the Investor

The risk-aversion level of the transmission system operator (investor) has a remarkable impact on the amount of market-integrable wind resources, as can be seen in Fig. 5. Note that a risk-aversion level ϑ equal to 1 corresponds to the extreme situation in which decision variables are just optimized for the worst-case scenario. A risk-averse system operator $(\vartheta > 0)$ seeks to guarantee the recovery of the transmission investment within the stipulated period. For this, the system operator reduces the capacity of the line to be built, thus limiting the amount of wind resources that can be potentially exploited. Again, observe that wind resources that are positively correlated with the electricity consumption can be more economically exploited and consequently, their exploitation call for transmission investment projects that are less risky. The proposed decision support tool is therefore able to discriminate *good winds*.

D. Subsidies

Let us suppose next that the wind power producer will receive a production tax credit of $\$t$/MWh. In such a case, the wind producer will compete in the electricity market with a marginal production cost given by $r_1 - t$. Fig. 6 shows the wind power production that is expected to be integrated in the market as a function of t. The transmission system operator is assumed to be risk averse with $\vartheta = 0.4$. Two general conclusions can be drawn from Fig. 6. First, production tax credits may make competitive the exploitation of wind resources that, in principle, are not economically attractive (see the plot corresponding to the base case). This is, logically, a direct consequence of the fact that production tax credits increase the market value of wind. Second, the impact of production tax credits on investment decisions and wind integration may be strongly dependent on the characteristics of the wind site to be exploited (notice how different this impact is in the two considered cases). The proposed decision support tool is, in this respect, able to quantify the specific effect of production tax credits on the competitiveness degree of a given wind project.

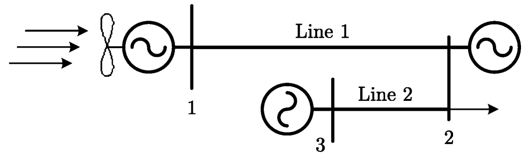

Fig. 7. Three-bus power system.

E. Network Cost Allocation Scheme

Until now, we have assumed that the transmission investment costs are recovered by solely charging the wind producer for the use of the new transmission facilities. Logically, if other system agents, such as consumers, are made to share these costs, wind integration is naturally boosted. For instance, if half of the cost of the transmission investment in the base case is passed on to the load at node 2, the expected amount of market-integrable wind resources increases from 196.7 MW to 265 MW. Needless to say, if the total costs of network investments were *inelastically* borne by the consumers, all wind resources would be equally exploitable within a market environment from a purely transmission-cost viewpoint.

F. Power System Configuration

Consider the three-node system in Fig. 7, which has been obtained by adding one bus, one line, and one conventional generating unit to the original two-node system in Fig. 2. Assume that the first four energy blocks listed in Table II (cheap blocks) correspond to the supply cost function of the unit located at node 3, while the rest of them (expensive blocks) correspond to the supply cost function of the unit at bus 2. If the capacity of line 2 is large enough, the solution for this modified case is equal to that for the base case. However, if the capacity of this line is limited to, e.g., 200 MW, then the amount of wind resources that is expected to be integrated in the electricity market increases from 196.7 to 237.4 MW. This is a straightforward example of the importance of the power system configuration and characteristics in the market integration of wind power.

G. Computational Performance

In order to easily illustrate the computational performance of the proposed solution procedure, without having to resort to cumbersome input data sets, we increase the number of wind power scenarios from three to one thousand, using the scenario generation procedure described in [25]. We emphasize that this is a remarkable increase, especially if compared with the number of scenarios that is being currently used in the technical literature (see e.g., [10]). To generate wind power scenarios, we assume that the speed of local winds at node 1 in Fig. 2 follows a Weibull distribution with scale and shape parameters equal to 9.7 and 1.6, respectively. Also, we consider that, technically speaking, 300 2.5-MW wind turbines, model Nordex N80/2500 with a hub height of 105 m, can be potentially installed in the wind site. The power curve of this turbine model can be found in [30]. Besides, we assume that the transmission investment is spread over five years and its cost is given by $I_y = (6-y)\cdot 10^4\, C_1^{\max}$ (\$) with $y = 1, \ldots, 5$. The three demand levels listed in Table I, namely, 1200, 800, and 200 MW, are used for this performance test, with probabilities of occurrence equal to 0.25, 0.50, and 0.25, in that order. This way, problem (5) becomes large-scale with more than 300 000 constraints and more than 500 000 variables. Both the master mixed-integer programming problem (7) and the linear programming subproblems (8) are solved using CPLEX 9.0.2 under GAMS [31] on a Windows-based personal computer Intel(R) Core(TM) i5 with 6 GB of RAM. The required computational time is smaller than 1 h and 44 min, which is reasonable considering that the decision framework proposed in this paper is intended to be used for planning purposes. Further, this time can be reduced by using parallel computation to exploit the fact that the problem can be decomposed into payback periods. The solution to this problem is $C_1^{\max} = 602$ MW, $r_1 = r_2 =$ \$20/MWh, $r_3 =$ \$12/MWh, and $r_4 = r_5 =$ \$7/MWh.

V. Conclusion and Future Work

This paper proposes a methodology to quantify the amount of wind resources at a given location that can be exploited through market competition, while accounting for the costs of the transmission investments required to provide the wind site with access to the meshed grid. We show that the competitiveness degree of a certain wind site is not only dependent on the cost of the transmission investment, but also on other factors such as wind and demand correlation, risk aversion of the system operator, allocation of transmission costs, subsidy schemes, and network congestion. The proposed methodology may be useful for power system operators to identify competitive wind sites and prioritize transmission investments.

Natural extensions of the research developed in this paper are, for instance, the implementation of a multi-stage setup to consider multiple wind projects to be carried out sequentially in time and the modeling of dynamic constraints, such as ramping limits of conventional generators, inasmuch as the inability of a power system to efficiently accommodate wind power variations may be detrimental to the competitiveness of wind producers. It would be also very interesting to couple the TSO problem dealt with in this paper with the capacity expansion problem of a wind power producer using, e.g., game theory analysis. Likewise, the modeling of "dynamic line rating" to account for the increment of the line current-carrying capacity in windy conditions is a subject that requires further research.

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