Optimal Offering Strategies for Wind Power Producers Considering Uncertainty and Risk

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***Abstract*—This paper provides a two-stage stochastic programming approach for the development of optimal offering strategies for wind power producers. Uncertainty is related to electricity market prices and wind power production. A hybrid intelligent approach, combining wavelet transform, particle swarm optimization and adaptive-network-based fuzzy inference system, is used in this paper to generate plausible scenarios. Also, risk aversion is explicitly modeled using the conditional value-at-risk methodology. Results from a realistic case study, based on a wind farm in Portugal, are provided and analyzed. Finally, conclusions are duly drawn.**

***Index Terms*—Artificial intelligence, forecasting, risk analysis, stochastic programming, uncertainty, wind power.**

NOMENCLATURE

S, s	Set and index of scenarios.
H, h	Set and index of hours in the time horizon.
ζ	Value-at-risk.
α	Per unit confidence level.
η_s	Auxiliary variable used to compute the conditional value-at-risk.
β	Weighting parameter to achieve an appropriate tradeoff between profit and risk.
ρ_s	Probability of occurrence of scenario s.
λ_{sh}	Forecasted electricity market price in scenario s in period h.
r^+_{sh}	Ratio between positive imbalance price and day-ahead market price in scenario s in period h.
r^-_{sh}	Ratio between negative imbalance price and day-ahead market price in scenario s in period h.
p_{sh}	Power output of the wind farm in scenario s in period h.
x_h	Offer by the wind power producer in the day-ahead market for period h.
dev_{sh}	Deviation for wind production in scenario s in period h.
$Pdev_{sh}$	Penalization for deviation of the wind farm in scenario s in period h.
W_{sh}	Forecasted wind power production in scenario s in period h.
$P^{\max}$	Maximum power of the wind farm.
L_{sh}	Revenue in scenario s in period h.
c	Vector of the objective function coefficients.
x	Vector of decision variables in the first-stage.
A	Matrix of coefficients for the first-stage constraints.
$b^{\min}$	Lower bound vector for the first-stage constraints.
$b^{\max}$	Upper bound vector for the first-stage constraints.
$x^{\min}$	Lower bound vector on variables.
$x^{\max}$	Upper bound vector on variables.
$h^{\min}_{\omega}$	Lower bound vector for the second-stage constraints.
$h^{\max}_{\omega}$	Upper bound vector for the second-stage constraints.
q_{ω}	Vector of coefficients for the linear term for the second-stage variables.
T_{ω}	Technology matrix.
W_{ω}	Recourse matrix.
y_{ω}	Second-stage variables that represent decisions to be made after part of the uncertainty is revealed.

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I. INTRODUCTION

AMONG THE renewable energy technologies, wind turbine technology is now the world's fastest growing energy resource [1], [2]. The increased integration of wind power into the power grid, as nowadays occurs for instance in Portugal, presents several technical challenges [3] due to its intermittency [4]. Unlike thermal systems [5] or hydro systems [6], which are traditional dispatchable power sources, wind power is undispatchable [7] and constitutes a major source of uncertainty in the planning and operations of power systems.

All over the world, the electricity industry is shifting from regulated to competitive. Until recently, the electricity industry was viewed as a natural monopoly, organized as regulated and vertically-integrated. Nowadays, the electricity industry adopted a market framework, thus introducing competition between producers for selling electric energy to consumers.

Under this market framework, the development of optimal offering strategies is crucial for all producers to achieve maximum profit. Background on market operations in power systems can be found, for instance, in [8].

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Electricity prices present high volatility, reflecting the dynamic behavior of the market. Besides, the power supply generated from wind energy is highly intermittent. Thus, decision-makers must hedge against the uncertainties on electricity market prices and wind power production, while taking into account the several technical constraints associated with the operation of the wind farm.

To consider the uncertainties on electricity market prices and wind power production requires stochastic programming [9]. Hence, in this paper a two-stage stochastic programming approach is presented, dividing the set of decisions inherent to the problem into two distinct stages: first-stage decisions, taken before resolving the uncertainty, second-stage decisions, made after the uncertainty occurs.

The aforementioned uncertainties were handled in [10] through traditional time-series models. Instead, an artificial intelligence model is considered in this paper to generate price-wind power scenarios using a tree format.

A scenario tree represents the different stages that can take the random parameters, i.e., different realizations of uncertainty. This scenario tree can be adequately trimmed via scenario reduction techniques [11], so that the resulting optimization problem is tractable.

Risk aversion is also incorporated in the proposed stochastic programming approach by limiting the volatility of the expected profit through the conditional value-at-risk (CVaR) methodology [12]–[14].

The proposed approach allows generating the optimal offers that should be submitted to the day-ahead market by a wind power producer, in order to maximize its expected profit assuming a given level of risk. In case of excessive or moderate offers, other producers must reduce or increase production to fill the so-called deviation, causing economic losses. These economic losses are reflected into imbalance penalties in the balancing market.

This paper is organized as follows. Section II presents the formulation of the risk-constrained profit-maximization decision-making problem faced by a wind power producer within the market framework. Section III describes the stochastic programming approach, including the decision framework, the uncertainty characterization, and the scenario tree. Section IV provides and analyzes results from a realistic case study, based on a wind farm in Portugal. Finally, Section V draws appropriate conclusions.

II. Problem Formulation

The optimization problem can be stated as to find out the:

1) offers submitted to the day-ahead market;
2) wind power production;
3) maximum profit at a given risk level;
4) imbalance penalties.

The problem formulation uses an absolute value function, since it can be expressed in the context of linear programming by adding some auxiliary variables for positive and negative deviations.

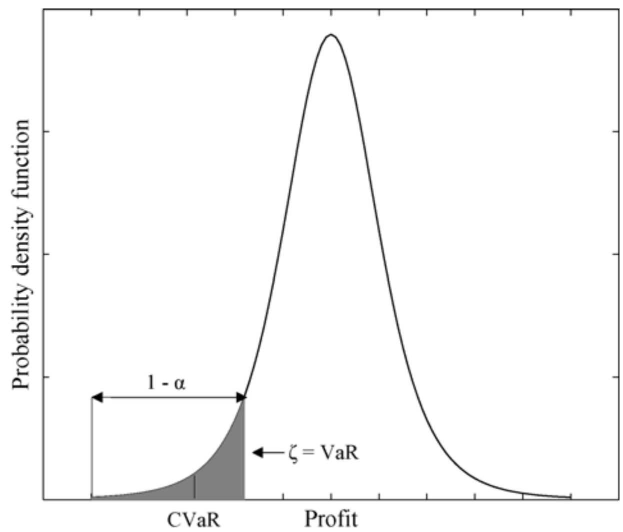

Fig. 1. VaR and CVaR illustration.

A. Risk Measure (CVaR)

CVaR represents an appropriate approach to address the integrated risk management problem of a wind power producer. Previous approaches [15]–[17] did not consider risk management.

CVaR is the expected profit not exceeding a measure ζ called value-at-risk (VaR)

$$\text{CVaR} = E(B|B \leq \zeta). \tag{1}$$

VaR is a measure computed as the maximum profit value such that the probability of the profit being lower than or equal to this value is lower than or equal to $1-\alpha$

$$\text{VaR} = \max\left\{x|\text{p}\left(B \leq x\right) \leq 1-\alpha\right\}. \tag{2}$$

VaR has the additional difficulty, for stochastic problems, that it requires the use of binary variables for its modeling. Instead, CVaR computation does not require the use of binary variables and it can be modeled by the simple use of linear constraints.

The concept of CVaR is illustrated in Fig. 1. The technical literature refers that α assumes values usually between 0.9 and 0.99 [18]. In this paper, α is considered equal to 0.95.

Mathematically, CVaR can be defined as follows:

$$\max \quad \zeta - \frac{1}{1-\alpha} \sum_{s=1}^{S} \rho_s \eta_s \tag{3}$$

subject to

$$-B_s + \zeta - \eta_s \leq 0 \tag{4}$$

$$\eta_s \geq 0. \tag{5}$$

In (4), η_s is a variable which is equal to zero if scenario s has a profit greater than ζ. For the remaining scenarios, η_s is equal to the difference of ζ and the corresponding profit.

B. Objective Function

The risk-constrained profit-maximization decision-making problem faced by a wind power producer within the market framework is summarized as follows:

$$F = \sum_{s=1}^{S} \rho_s \sum_{h=1}^{H} \left[\lambda_{sh}\ p_{sh} - Pdev_{sh}\right] + +\beta\left(\zeta - \frac{1}{1-\alpha}\sum_{s=1}^{S}\rho_s \eta_s\right). \tag{6}$$

The objective function (6) to be maximized includes the expected profit of the wind power producer, and the CVaR of the profit multiplied by the weighting parameter β.

The objective function represents the total profit on the sale of wind energy in each scenario s, taking into account the probability of occurrence ρ_s, less a penalty for deviations from the bids, in which λ_{sh} is the forecasted electricity market price in scenario s in period h. The deviations are measured in absolute value, and can be generated by excess or deficit of energy

$$dev_{sh} = |p_{sh} - x_h|. \tag{7}$$

The penalty for the deviation corresponds to the product of the cost for the shifted power in absolute value

$$Pdev_{sh} = \begin{cases} \lambda_{\text{sh}}\ r^+_{sh}\ dev_{sh}, & dev_{sh} \geq 0 \\ \lambda_{\text{sh}}\ r^-_{sh}\ dev_{sh}, & dev_{sh} < 0\ . \end{cases} \tag{8}$$

The revenue is given by the product of the expected market price by the power output of the wind farm

$$L_{sh} = \lambda_{sh}\ p_{sh}. \tag{9}$$

The expected profit is calculated as the difference between the revenue of the wind farm and the penalization for deviation

$$F = L_{sh} - Pdev_{sh}. \tag{10}$$

Substituting (8) into (6) gives

$$F = \sum_{s=1}^{S} \rho_s \sum_{h=1}^{H} \left[\lambda_{sh}\ p_{sh} - \lambda_{sh}\ r^+_{sh}\ d^+_{sh} - \lambda_{sh}\ r^-_{sh}\ d^-_{sh}\right] + +\beta\left(\zeta - \frac{1}{1-\alpha}\sum_{s=1}^{S}\rho_s \eta_s\right). \tag{11}$$

C. Constraints

For a given total energy deviation $dev_{sh} = d^+_{sh} - d^-_{sh}$ the optimal solution is guaranteed to be achieved with one of the variables d^+_{sh} or d^-_{sh} equal to zero, due to the fact that $r^+_{sh} \leq 1$ and $r^-_{sh} \geq 1$

$$p_{sh} - x_h - d^+_{sh} + d^-_{sh} = 0. \tag{12}$$

In order to make the offers to the market, it is required to satisfy the technical restrictions of the wind farm.

So, the optimal value of the objective function is determined subject to inequality constraints or simple bounds on the variables.

The constraints are indicated as follows:

$$0 \leq d^+_{sh} \leq W_{sh} \tag{13}$$

$$0 \leq d^-_{sh} \leq P^{\max}. \tag{14}$$

Constraints (13) and (14) impose caps on the positive and negative deviations, respectively. Wind power is limited superiorly by the value of the forecasted wind power production, W_{sh}, in scenario s in period h.

In (15), the offers are limited by the maximum power installed in the wind farm $P^{\max}$

$$0 \leq x_h \leq P^{\max}. \tag{15}$$

In (16), η_s is a variable whose value is equal to zero if the scenario s has a profit greater than ζ. For the rest of scenarios, η_s is equal to the difference of ζ and the corresponding profit

$$-\sum_{h=1}^{H}\left[\lambda_{sh}\ p_{sh} - \lambda_{sh}\ r^+_{sh}\ d^+_{sh} - \lambda_{sh}\ r^-_{sh}\ d^-_{sh}\right] + \zeta - \eta_s \leq 0 \tag{16}$$

$$\eta_s \geq 0. \tag{17}$$

D. Linearization of the Objective Function

The objective function, given in the previous subsection, is characterized by nonlinearities due to the existence of an absolute value. So, it is required to use a mathematical process that allows reformulating into a linear problem.

In this subsection, the problem involving absolute value terms is transformed into a standard linear programming formulation. Initially, it is considered that

$$\text{Max}\ \ F = c^{\mathrm{T}}x - |\ x\ | \tag{18}$$

subject to

$$x^{\min} \leq x \leq x^{\max} \tag{19}$$

$$x \in \mathrm{R}^{\mathrm{n}}. \tag{20}$$

In (18), the function $F(\cdot)$ is an objective function of decision variables, where c is the vector of coefficients for the linear term.

In (19), $x^{\min}$ and $x^{\max}$ are the lower and upper bound vectors on variables. The variable x is a set of decision variables.

Subsequently, absolute-valued variables are replaced with two strictly positive variables

$$|\ x\ | = x^+ + x^-. \tag{21}$$

In addition, each variable is substituted by the difference of the same two positive variables, as

$$x = x^+ - x^-. \tag{22}$$

The equivalent linear programming problem is given by

$$\text{Max}\ \ F = c^{\mathrm{T}}x - (x^+ + x^-) \tag{23}$$

subject to

$$x^{\min} \leq x \leq x^{\max} \tag{24}$$

$$x = x^+ - x^- \tag{25}$$

$$x^+ \geq 0\ ,\ x^- \geq 0. \tag{26}$$

III. Stochastic Programming Approach

A. Decision Framework

A time horizon of one day is considered. Within this time horizon the wind power producer must decide: 1) hourly offers to be submitted to the day-ahead market, and 2) wind power production in each hour for a given scenario.

Within the stochastic programming approach, two different kinds of decisions can be distinguished.

On the one hand, the decisions that are made before knowing the actual values of the stochastic variables are known as first-stage or here-and-now decisions, since we have to make them before knowing the actual scenario realization. These decisions correspond to the hourly offers to be submitted to the day-ahead market.

On the other hand, the decisions that are made after knowing the actual values of the stochastic variables are known as second-stage or wait-and-see decisions, since we assume that the corresponding scenario has realized before making such decisions. These decisions correspond to the wind power production in each hour for a given scenario.

B. Uncertainty Characterization

Uncertainties of electricity market prices and wind power production are handled by treating them as stochastic variables. To generate price and wind power scenarios, time-series-based models, such as ARIMA [10], or artificial intelligence models, such as neural networks [19], data mining [20] and evolutionary computation [21], can be used.

A hybrid intelligent approach, combining wavelet transform (WT), particle swarm optimization (PSO) and adaptive-network-based fuzzy inference system (ANFIS), is used in this paper to generate a large enough number of equiprobable scenarios, that adequately represent the probability distribution of electricity market prices and wind power production over the day.

The WT convert a wind power or price series in a set of constitutive series, forecasted using ANFIS. The PSO is used to improve the performance of ANFIS, tuning the membership functions required to achieve a lower error. Indeed, PSO has turned out to be an outstanding optimizer due to its ability to elegantly handle difficult optimization problems as well as its exceptional convergence performance [22]–[24].

C. Scenario Tree

A scenario tree is a set of nodes and branches used in models of decision-making under uncertainty. The nodes represent the points where decisions are made, while the branches are different realizations of the stochastic variables. Each node has only one predecessor and can have several successors. The first node is called the root node. In the root node, the first-stage decisions are taken. The nodes in the last stage are called leaves. The number of leaves equals the number of scenarios [25], [26].

Fig. 2 shows the scenario tree that is used to represent the first-stage and second-stage decisions.

For the sake of problem tractability, it may be convenient to reduce the size of the scenario tree. The scenario tree trimming consists in finding a new tree composed by a subset of scenarios belonging to the original tree that is close to the original tree according to a specific probability distance.

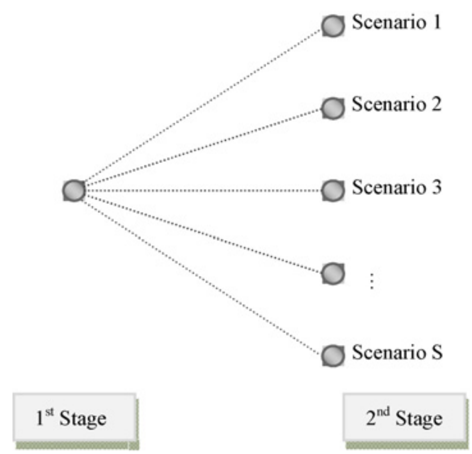

Fig. 2. Scenario tree.

A scenario-reduction technique provides an efficient way to select a representative subset of scenarios covering most scenario realizations, plausible and extreme.

A fast-forward reduction algorithm is described in [11]. This algorithm is an iterative greedy process starting with an empty tree that in each iteration selects the scenario which minimizes the probability distance between the original and the reduced trees.

D. Two-Stage Stochastic Programming

The two-stage stochastic programming model can be formulated as follows:

$$\text{Max} \quad c^{\mathrm{T}} x + E[\max_{y_\omega} q_\omega^{\mathrm{T}}\, y_\omega] \tag{27}$$

subject to

$$b^{\min} \leq Ax \leq b^{\max} \tag{28}$$

$$h_\omega^{\min} \leq T_\omega\, x + W_\omega\, y_\omega \ \leq h_\omega^{\max} \tag{29}$$

$$x \geq 0,\, y_\omega \ \geq 0 \tag{30}$$

where c is a vector of the objective function coefficients for the x variables in the first-stage, $b^{\min}$ and $b^{\max}$ are the lower and upper bound vectors for the first-stage constraints, and A is the matrix of coefficients for the first-stage constraints. For each ω, $h_\omega^{\min}$ and $h_\omega^{\max}$ are the lower and upper bound vectors for the second-stage constraints, q_ω is vector of coefficients for the linear term for the second-stage variables, T_ω is the technology matrix, and W_ω is the recourse matrix under scenario ω.

In the first stage, the decision should be taken before the uncertainties represented by x are known. In the second stage, where the information x is already available, the decision is made about the vector y.

The first-stage decision of x depends only on the information available until that time; this principle is called nonanticipativity constraint.

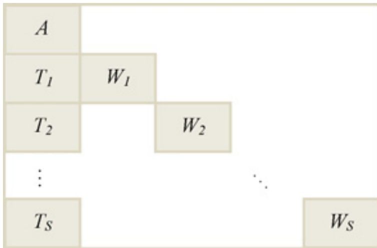

Fig. 3. Layout of the constraints associated with two stages.

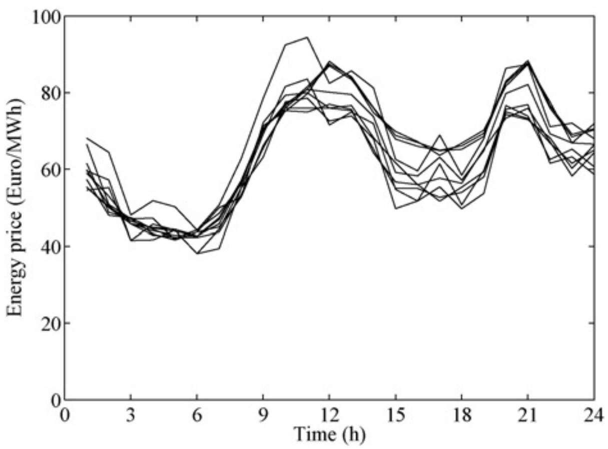

Fig. 4. Electricity market price scenarios considered in the case study.

The problem of two stages means that the decision x is independent of the achievements of the second stage, and thus the vector x is the same for all possible events that may occur in the second stage of the problem.

E. Deterministic Equivalent Problem

The stochastic model is usually a difficult computational problem, so it is common to choose the deterministic model solution using the average of random variables or solving a deterministic problem for each scenario.

The problem shown in the previous subsection is equivalent to the so-called deterministic equivalent one that in the splitting variable representation is as follows:

$$\mathrm{Max}_{\mathrm{x},\mathrm{y}_\mathrm{s}} \quad c^{\mathrm{T}}x + \sum_{\mathrm{s}=1}^{\mathrm{S}} \rho_{\mathrm{s}} q_{\mathrm{s}}^{\mathrm{T}} y_{\mathrm{s}} \tag{31}$$

subject to

$$b^{\min} \leq Ax \leq b^{\max} \tag{32}$$

$$h_s^{\min} \leq T_s\, x + W_s\, y_s \ \leq h_s^{\max} \quad \text{for } s = 1, \ldots, S \tag{33}$$

$$x \geq 0,\, y_s \ \geq 0 \quad \text{for } s = 1, \ldots, S. \tag{34}$$

The matrix composed by (32) and (33), for large-scale linear problems, can be generally represented according to Fig. 3.

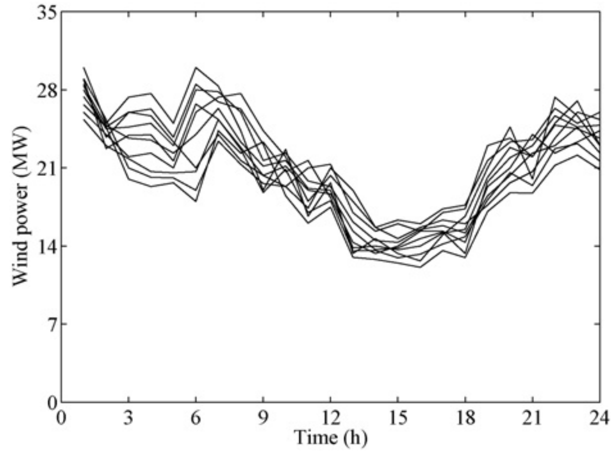

Fig. 5. Wind power scenarios considered in the case study.

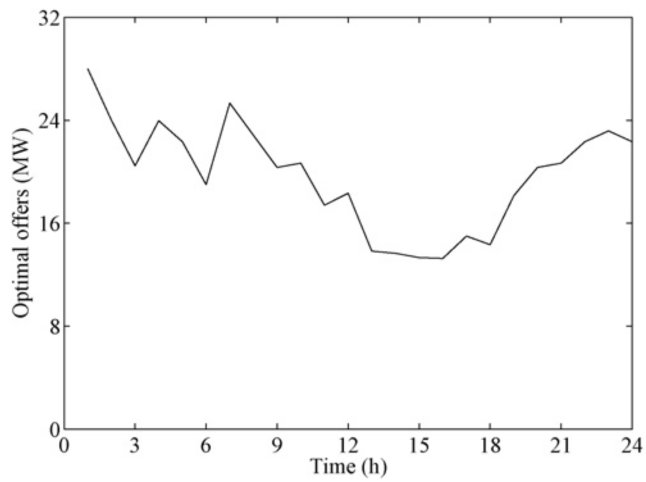

Fig. 6. Optimal hourly bids for a risk level corresponding to $\beta = 0.2$.

IV. Case Study

The proposed approach has been developed and implemented in MATLAB, and solved using the optimization solver package CPLEX. The numerical simulation has been performed on a 2 GHz based processor with 2 GB of RAM.

The proposed approach has been applied on a realistic case study, based on a wind farm in Portugal located in the Castelo Branco region (Gardunha). The total installed wind power capacity is 114 MW, corresponding to 57 2.0 MW wind turbines.

The proposed approach takes into account the uncertainty in both wind power and electricity market prices by using scenarios in a stochastic optimization problem. Imbalance penalties are imposed to prevent gaming and to secure better system operation [27].

The time horizon chosen is one day divided into 24 hourly periods. This case study is composed of ten electricity market prices scenarios (Fig. 4) and ten wind power scenarios (Fig. 5).

Besides, ten imbalance price ratio scenarios are taken into account. Thus, the total number of scenarios generated in the optimization problem is $S = 1000$. The probability of each generated scenario will be $1/S$. Table I summarizes the data of the scenarios.

TABLE I
SCENARIOS CONSIDERED, NUMBER, AND PROBABILITY

	Number of Scenarios	Probability
Price scenarios	10	0.10
Wind scenarios	10	0.10
Imbalance price ratio scenarios	10	0.10
Total scenarios	1000	0.001

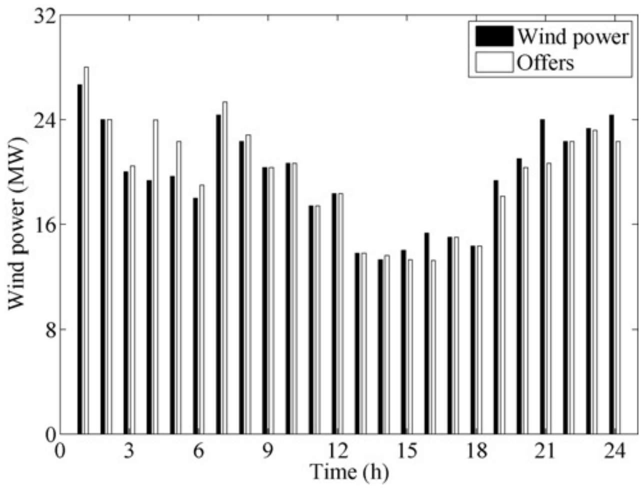

Fig. 7. Optimal offers to be submitted to the day-ahead market, and wind power production, for a risk level corresponding to $\beta = 0.2$.

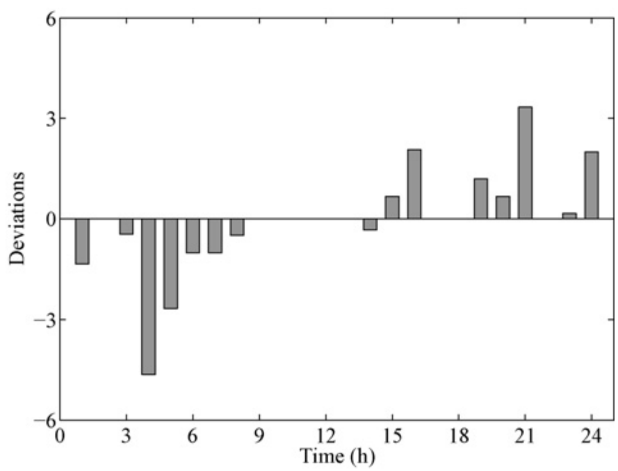

Fig. 8. Deviations resulting from the difference between the offers and the wind power production for a risk level corresponding to $\beta = 0.2$.

The solution of the optimization model contains the optimal bids for the daily market. The optimal bids, shown in Fig. 6, are common to the 1000 scenarios, thus posing a robust solution against all of them, although not necessarily optimal in any one.

Choosing one scenario of the problem, it can be verified in Fig. 7 that the wind farm adjusts its production to minimize deviations. Nevertheless, in almost every hour there are small differences between the offers and the power output of the wind farm.

The deviations resulting from the difference between the offers and the wind power production are shown in Fig. 8. For instance, a negative deviation means that the wind power production was lower than the offer submitted to the day-ahead market.

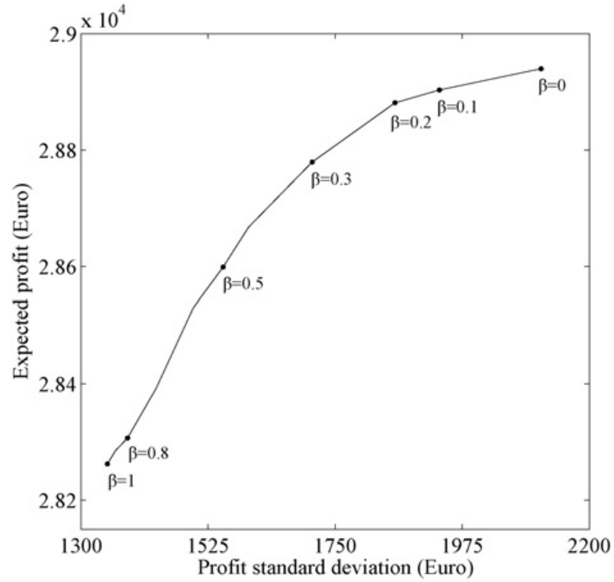

Fig. 9. Expected profit versus profit standard deviation.

TABLE II
COMPARISON OF THE INCREASE IN PROFIT FOR SEVERAL RISK LEVELS

Risk Level	Profit Standard Deviation (€)	Expected Profit (€)	% Increase	CPU Time (s)
1.0	1347	28 262	–	1.45
0.9	1361	28 285	0.08	1.31
0.8	1382	28 306	0.16	1.22
0.7	1433	28 391	0.46	1.13
0.6	1499	28 529	0.94	1.05
0.5	1552	28 599	1.19	0.98
0.4	1596	28 667	1.43	0.94
0.3	1709	28 779	1.83	0.91
0.2	1856	28 881	2.19	0.89
0.1	1934	28 903	2.27	0.80
0.0	2114	28 939	2.40	0.75

The expected profit versus profit standard deviation is presented in Fig. 9, considering seven values for β. A confidence level $\alpha = 0.95$ is used to compute the CVaR in all instances.

Fig. 9 provides the maximum achievable expected profit for each risk level or, alternatively, the minimum achievable level of risk for each expected profit. This figure, known as efficient frontier or Markowitz frontier, presents a curve that contains a set of solutions to help the wind power producer in decision-making taking into account the intermittency and volatility of wind power and the uncertainty of electricity prices.

The main objective is to provide a portfolio with various risk levels. Each level of risk implies a different expected profit and its associated standard deviation.

An analysis of Fig. 9 reveals that for a risk-neutral producer ($\beta = 0$) the expected profit is 28 939 € with a standard deviation of 2114 €. Instead, a risk-averse producer ($\beta = 1$) expects to achieve a profit of 28 262 € with a lower standard deviation of 1347 €.

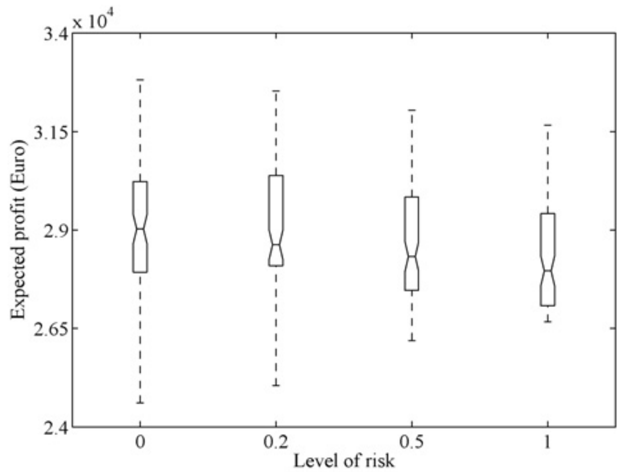

Fig. 10. Dispersion of profit for different risk levels.

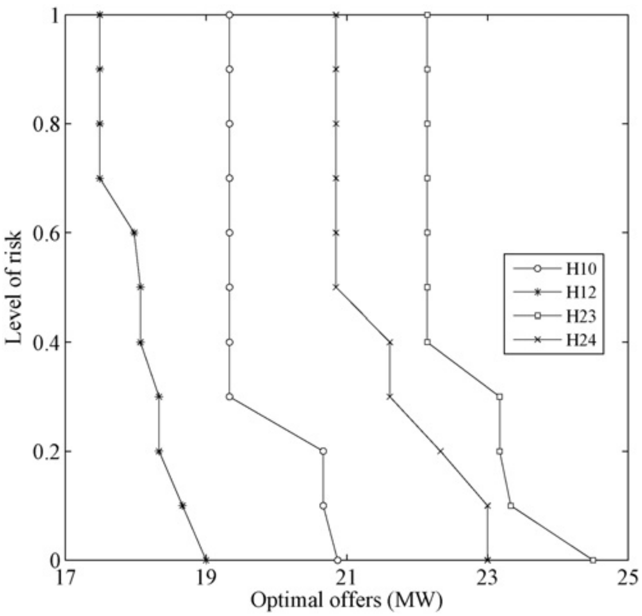

Fig. 11. Level of risk versus optimal offers for hours 10, 12, 23, and 24.

Table II establishes a numerical comparison of the increase in profit for several risk levels. The maximum profit represents an increase of 2.40% corresponding to risk level $\beta = 0$. Nevertheless, the profit standard deviation is significantly higher for $\beta = 0$. Hence, the wind power producer may choose different behaviors toward risk. Based on the results obtained, the risk level suggested is between $\beta = 1$ and $\beta = 0.4$. Risk levels lower than or equal to $\beta = 0.3$ are not recommended.

Also, according to the results, it appears that the proposed approach is influenced by the volatility of the stochastic variables involved in the optimization process (intermittency and volatility of wind power and the uncertainty of electricity prices).

In this sense, it is concluded that the higher the volatility, the more advantageous is the use of stochastic methodologies supported by prediction tools. Stochastic programming can increase the expected value of profit distribution, keeping under control the risk of profit variation.

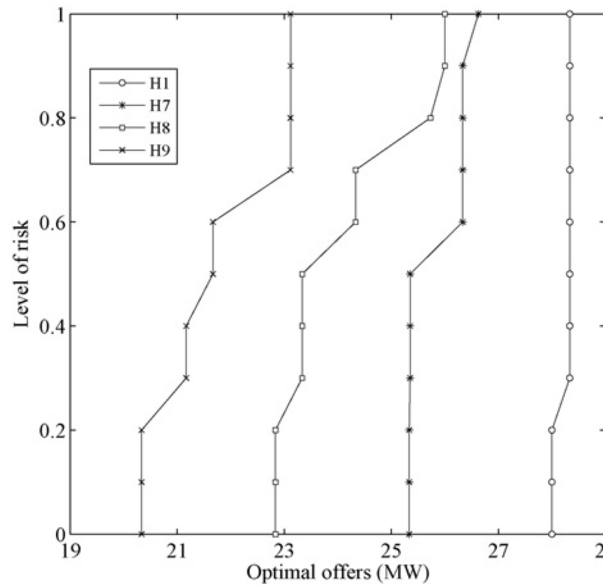

Fig. 12. Level of risk versus optimal offers for hours 1, 7, 8, and 9.

The dispersion of profit for the 1000 scenarios is shown in Fig. 10.

The expected profit is higher for $\beta = 0$, but the dispersion of profit is also much more relevant compared with other risk levels. Instead, the lowest dispersion of profit is attainable for $\beta = 1$. Hence, a more conservative wind power producer toward risk expects a lower variability of the expected profit.

Figs. 11 and 12 provide the variation in the risk level in relation to the offers submitted by the wind power producer. It can be seen that, depending on the particular hour considered, the behavior of the curve can assume a different tendency.

V. Conclusion

Aiming for adequate decision-support tools for a wind power producer under different uncertainties, related to electricity market prices and wind power production, a stochastic programming approach was proposed in this paper, along with a hybrid intelligent approach to generate price-wind power scenarios. Risk aversion is also incorporated by limiting the volatility of the expected profit through the CVaR methodology. The proposed approach allows evaluating alternative production and offering strategies to be submitted to the market. A realistic case study, based on a wind farm in Portugal, is considered. It can be concluded that a better short-term operation of the wind farm is achieved, assuring simultaneously a negligible computation time.

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