A risk-averse optimization model for trading wind energy in a market environment under uncertainty

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Abstract

In this paper, a stochastic programming approach is proposed for trading wind energy in a market environment under uncertainty. Uncertainty in the energy market prices is the main cause of high volatility of profits achieved by power producers. The volatile and intermittent nature of wind energy represents another source of uncertainty. Hence, each uncertain parameter is modeled by scenarios, where each scenario represents a plausible realization of the uncertain parameters with an associated occurrence probability. Also, an appropriate risk measurement is considered. The proposed approach is applied on a realistic case study, based on a wind farm in Portugal. Finally, conclusions are duly drawn.

Keywords: Wind energy; Stochastic programming; Uncertainty; Risk-aversion

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1. Introduction

The use of renewable energies has been increasing in the last decade worldwide [1], particularly in European countries such as Denmark [2,3] and Ireland [4]. Large-scale renewable energy implementation plans must include strategies for integrating renewable sources in energy systems influenced by energy savings and efficiency measures [5]. Concerning renewable energies, hydro [6] and wind [7] energy are the main priorities in the Portuguese energy policy.

The Portuguese energy sector underwent a significant restructuring during 2006, as a result of the implementation of European Union (EU) Directives on electricity and gas of the European Parliament and Council. The main objectives of this restructuring are:

(i) to safely guarantee the supply of energy to Portugal, through the diversification of the primary resources used, namely by reinforcing the development of renewable energy sources, and through the promotion of efficiency;

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(ii) to stimulate and favor competition in a way as to promote consumer protection, as well as the competitiveness and efficiency of the Portuguese companies operating in the energy sector and in the national production sector;

(iii) to ensure the energy sector meets certain environmental standards, reducing the environmental impact at the local, national and global levels.

A variety of primary sources and technologies are used in power plants, namely coal, gas, fuel, water and wind, among others. The total installed capacity in Portugal at end of year 2009 reached 16738 MW, of which 6690 MW (40%) corresponded to thermal power plants, 4578 MW (27%) corresponded to hydro power plants, and 3357 MW (20%) corresponded to wind power plants. The wind power capacity target is 5500 MW by 2012, and 8500 MW by 2020, augmenting considerably the role that wind energy plays in electricity generation.

The electricity industry in Portugal can be divided into five major functions: generation, transmission, distribution, supply and demand, and market structure. Each of these functions must be operated independently, from a legal, organizational and decision-making standpoint, from the others [8]. Electricity generation is now fully open to competition, subject to obtaining the requisite licenses and approvals. Under a market framework, the development of optimal offering strategies is crucial for all producers to achieve maximum profit.

Energy prices in the wholesale spot market are inherently volatile and unpredictable, while the retail prices may or may not depend on the wholesale prices, at least in the short term. The high volatility of energy prices reflects the dynamic behavior of the spot market. Moreover, the power supply generated from wind energy is highly intermittent. Indeed, the outcome of fluctuations in wind energy sources produces a situation in which excess energy is sometimes generated, while at other moments there is a lack of generated energy [9]. Consequently, decision-makers must hedge against the uncertainties on energy market prices and wind power production, while taking into account the several technical constraints associated to the operation of the wind farm.

There are some approaches that allow dealing with the uncertainty in the energy market. For example, in the United States, there have been numerous studies that seek to develop financial instruments for the purpose of hedging against price uncertainty in the electricity spot market. Specifically, work has been done that uses cross-hedging in the natural gas forward market [10-13].

To consider the uncertainties on energy market prices and wind power production, a stochastic programming approach is used in this paper, as in [14,15], dividing the set of decisions inherent to the problem into two distinct stages: first-stage decisions, taken before resolving the uncertainty, and second-stage decisions, made after the uncertainty occurs.

Stochastic programming presents a set of solutions that take into consideration the randomness in input parameters. The stochastic programming approach has been used for a wide spectrum of applications [16], with the advantage of finding a near optimal solution considering all possible scenarios. The stochastic solution may not be a global optimal solution to the individual scenarios, but it is a robust solution over all possible realizations of the uncertainties.

The aforementioned uncertainties were handled in [17] 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. Each scenario represents the outcomes for a specific set of random-parameter values. This scenario tree can be adequately trimmed via scenario reduction techniques [18], 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 [19-21].

The proposed approach enables wind energy trading in a market environment under uncertainty, maximizing the expected profit of a wind power producer assuming a given risk level. 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 in imbalance penalties in the balancing market. Hence, the proposed approach allows dealing in the same optimization model with:

(i) Offers submitted to the day-ahead market;

(ii) Wind power production;

(iii) Profit maximization at a given risk level;

(iv) Imbalance penalties;

(v) Operational costs minimization.

The paper is structured as follows. Section 2 presents the mathematical formulation of the decision-making problem faced by a wind power producer in a market environment under uncertainty. Section 3 describes the proposed stochastic programming approach. Section 4 presents a case study, based on a wind farm in Portugal. Section 5 provides error analysis and, finally, Section 6 provides conclusions.

Nomenclature

S, s	Set and index of scenarios
H, h	Set and index of hours in the time horizon
I, i	Set and index of wind generators
ζ	Value-at-risk
α	Per unit confidence level
B_s	Profit in scenario s
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	Occurrence probability of scenario s
λ_{sh}	Forecasted energy 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
b_{ih}	Operational cost associated to wind turbine i at period h
g_{ih}	Power output of the wind turbine i 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
$Pdev_{sh}$	Penalty 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
$h_{\omega}^{\min}$	Lower bound vector for the second-stage constraints
$h_{\omega}^{\max}$	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

2. Problem formulation

2.1 Risk measure (CVaR)

CVaR represents an appropriate approach to address the integrated risk management problem of a wind power producer. Previous approaches [22-24] did not consider risk-aversion.

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

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

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 $1-\alpha$:

$$\text{VaR} = \max\{x \mid p(B \leq x) \leq 1-\alpha\} \tag{2}$$

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 value of α is commonly set between 0.90 and 0.99 [25]. In this paper, α is considered equal to 0.95.

"See Fig. 1 at the end of the manuscript".

The CVaR at α confidence level, $\alpha-\text{CVaR}$, is defined as the expected profit of the $(1-\alpha)\times 100\%$ scenarios showing lowest profit. Mathematically, CVaR can be defined as:

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

subject to:

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

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

In (4), B_s is the profit in scenario s, η_s is a variable whose value 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. In other words, η_s provides the excess of ζ over the profit in scenario s if this excess is positive. The constraints (4) and (5) are used to incorporate the risk metric CVaR.

2.2 Objective function

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

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

The objective function (6) to be maximized includes the expected profit, the operational costs, and the CVaR multiplied by the weighting factor β. The factor β models the tradeoff between the expected profit and the CVaR. The deviations are measured in absolute value, and can be generated by excess or deficit of energy:

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

The penalty for 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 energy 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, the penalty for deviation and the operational costs.

Substituting (8) into (6) gives:

$$F = \sum_{s=1}^{S} \rho_s \sum_{h=1}^{H} \left[\lambda_{sh}\ p_{sh} - \lambda_{sh}\ r_{sh}^{+}\ d_{sh}^{+} - \lambda_{sh}\ r_{sh}^{-}\ d_{sh}^{-} \right] - \sum_{h=1}^{H} \sum_{i=1}^{I} \left[b_{ih}\ g_{ih} \right] + \beta \left(\zeta - \frac{1}{1-\alpha} \sum_{s=1}^{S} \rho_s \eta_s \right) \tag{10}$$

2.3 Constraints

For a total 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 $r_{sh}^{+} \le 1$ and $r_{sh}^{-} \ge 1$:

$$p_{sh} - x_h - d_{sh}^{+} + d_{sh}^{-} = 0 \tag{11}$$

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:

$$0 \le d_{sh}^{+} \le W_{sh} \tag{12}$$

$$0 \le d_{sh}^{-} \le P^{\max} \tag{13}$$

Constraints (12) and (13) 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 (14), the offers are limited by the maximum power installed in the wind farm $P^{\max}$.

$$0 \le x_h \le P^{\max} \tag{14}$$

Constraint (15) imposes that offers should be lower than or equal to the total power output of the wind turbines.

$$x_h \le \sum_{i=1}^{I} g_{ih} \tag{15}$$

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.

$$-\sum_{h=1}^{H}\left[\lambda_{sh}\ p_{sh}-\lambda_{sh}\ r_{sh}^{+}\ d_{sh}^{+}-\lambda_{sh}\ r_{sh}^{-}\ d_{sh}^{-}-\sum_{i=1}^{I}\left(b_{ih}\ g_{ih}\right)\right]+\zeta-\eta_s\leq 0 \tag{16}$$

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

2.4 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 decisions variables.

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

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

Notice that either x^{-} is positive and x^{+} is zero, or x^{-} is zero and x^{+} positive, implying that a positive deviation leads to $x^{-}=0$ and a negative deviation implies $x^{+}=0$. Both x^{+} and x^{-} cannot be positive at the same time. Hence, 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:

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

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

$$x^{+} \ge 0 \quad , \; x^{-} \ge 0 \tag{26}$$

3. Proposed approach

3.1 Uncertainty characterization

Uncertainties of energy 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 [17], or artificial intelligence models, such as neural networks [26], data mining and evolutionary computation [27], 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 energy market prices and wind power production over the day.

The WT convert a price or wind power series into 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. The parameters of WT, PSO and ANFIS, and the step-by-step algorithm used to implement the proposed approach, are presented in [28].

The hybrid intelligent approach allows generating 1000 scenarios for the day-ahead market price, the wind power generation and the price for imbalance for each hour. The price scenarios are combined with wind power scenarios. The resulting set of scenarios is used to evaluate day-ahead bidding, market profits, and risk measures.

The uncertainty is modeled through a scenario tree that is built as follows:

1) Generate N_{λ} price scenarios for the day-ahead market;

2) For each scenario of the market prices, generate N_W wind power realizations;

3) For each wind power realization, simulate N_r imbalance price ratio scenarios.

Hence, the total number of scenarios composing the tree is $\mathrm{S} = N_{\lambda} N_W N_r$.

3.2 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 [29,30].

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

"See Fig. 2 at the end of the manuscript".

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.

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 [18]. 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.

3.3 Stochastic programming approach

In this subsection the standard stochastic linear programming approach is presented, which describes in general the problem formulation of the wind power producer. This problem can be solved through linear programming due to a linear transformation in the objective function broadly described in subsection 2.4.

Hence, the stochastic programming approach can be formulated as:

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

subject to:

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

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

$$x \ge 0 \ , \quad y_\omega \ge 0 \tag{30}$$

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. 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.

3.4 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:

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

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

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

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

"See Fig. 3 at the end of the manuscript".

4. Case study

The purpose of the paper is to develop a model that allows one to determine an efficient frontier of risk-return tradeoffs, which along with the tradeoffs that management is willing to accept between the two, provides management with a readily-implemented and easily understood procedure for making an optimal decision, in the sense of the decision that management prefers, given the opportunities available to it.

The simulation study provides a numerical example that has actually been applied in a real-world Portuguese setting, based on a wind farm located in the Viana do Castelo region (Alto Minho - Corisco). The total installed wind power capacity is 66 MW, corresponding to 33 2.0-MW wind turbines. Our model has been developed and implemented in MATLAB and solved using the optimization solver package CPLEX. The numerical testing has been performed on a 2-GHz-based processor with 2 GB of RAM.

4.1 Input data

The proposed approach takes into account the uncertainty in both wind power and energy market prices by using scenarios in a stochastic optimization problem. The profits of a wind power producer are evaluated according to a given risk level. Imbalance penalties are imposed to prevent gaming and to secure better system operation [31].

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

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Moreover, 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 1 summarizes the data of the scenarios.

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4.2 Result analysis

A thorough comparison of the optimal offering strategies in the market for different risk levels using the proposed approach is presented thereafter, highlighting the contributions modeled in this paper.

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. This figure shows the ability of the wind power producer to trade in the day-ahead market taking into account the desired risk level.

"See Fig. 6 at the end of the manuscript".

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.

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The deviations resulting from the difference between the offers and the wind power production are shown in Fig. 8. A positive deviation means that the wind power production was higher than the offer submitted to the day-ahead market, and vice-versa.

"See Fig. 8 at the end of the manuscript".

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 risk level for each expected profit. This figure, known as efficient frontier, reveals that for a risk-neutral producer $(\beta = 0)$ the expected profit is 18719 € with a standard deviation of 1268 €. Instead, a risk-averse producer $(\beta = 1)$ expects to achieve a profit of 18478 € with a lower standard deviation of 965 €.

"See Fig. 9 at the end of the manuscript".

Considering that each of the scenarios is equally likely to occur, 1000 combinations of those settings are developed, which enables us to derive the efficient frontier in Fig. 9. The decision maker ought to have previously been asked to provide a risk-preference curve from which one can derive the tradeoffs that s/he is willing to accept between expected profit and its variance (or standard deviation) as a (debatable) proxy for risk, with the optimal decision then being that which is associated with the point of tangency of that curve with the frontier. The underlying risk-preference function can be approximated by a quadratic function.

Table 2 establishes a numerical comparison of the increase in profit for several risk levels. The maximum profit represents an increase of 1.30% corresponding to risk level $\beta = 0$. Nevertheless, the profit standard deviation is higher for $\beta = 0$. Hence, the wind power producer may choose different behaviors towards risk.

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Fig. 10 and Fig. 11 present the histograms of the profits for $\beta = 0$ and $\beta = 0.5$, respectively.

"See Fig. 10 at the end of the manuscript".

"See Fig. 11 at the end of the manuscript".

Analyzing Fig. 10 and Fig. 11, it can be verified that the risk level corresponding to $\beta = 0$ implies a higher expected profit than for the risk level corresponding to $\beta = 0.5$. Nevertheless, $\beta = 0$ is riskier than $\beta = 0.5$ because financial loss can occur under some scenarios, thus a risk-averse producer would prefer $\beta = 0.5$. Our approach allows selecting the best solution according to the desired risk exposure level.

5. Error analysis

The volatility of the expected profit is analyzed by means of dispersion. Accordingly, the dispersion of profit for the 1000 scenarios is show in Fig. 12. Table 3 presents the confidence intervals of 95% regarding the expected profit.

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Although the expected profit is higher for $\beta = 0$, the dispersion of profit is also more relevant compared with other risk levels. Instead, the lowest dispersion of profit is attainable for $\beta = 1$. Hence, a risk-averse producer would expect a lower variability of the expected profit.

6. Conclusions

A stochastic programming approach is proposed in this paper, along with a hybrid intelligent approach to generate price-wind power scenarios, enabling wind energy trading in a market environment under uncertainty. The uncertainties are related to energy market prices and wind power production. Risk aversion is also incorporated by limiting the volatility of the expected profit through the CVaR methodology. A thorough comparison of the optimal offering strategies in the market for different risk levels is presented in this paper, illustrating the proficiency of the proposed approach on a realistic case study, while assuring an acceptable computation time.

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Figure captions

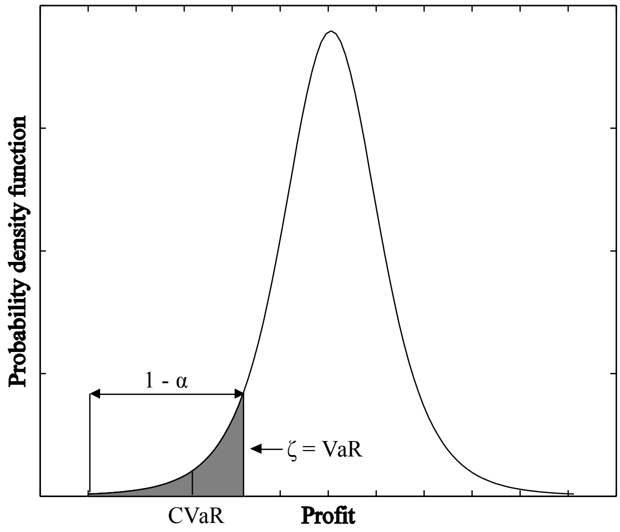

Fig. 1. VaR and CVaR illustration.

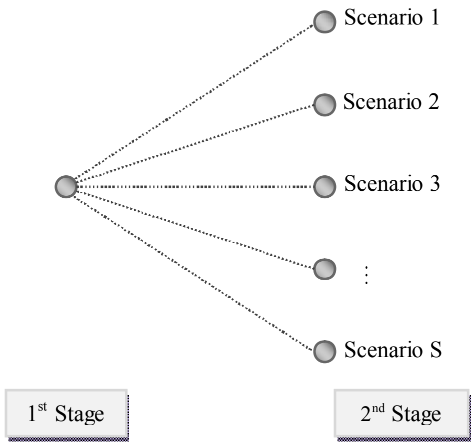

Fig. 2. Scenario tree.

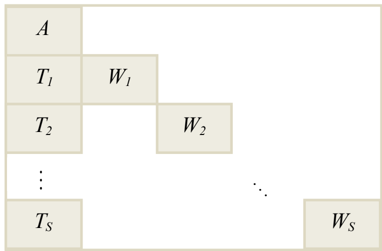

Fig. 3. Layout of the constraints associated with two stages.

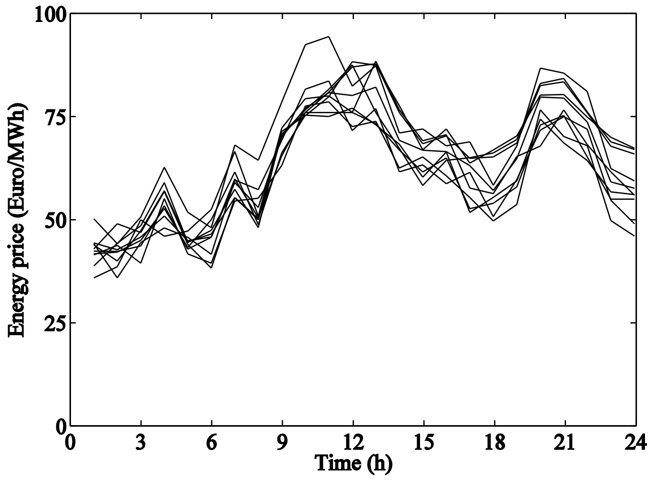

Fig. 4. Energy market price scenarios considered in the case study.

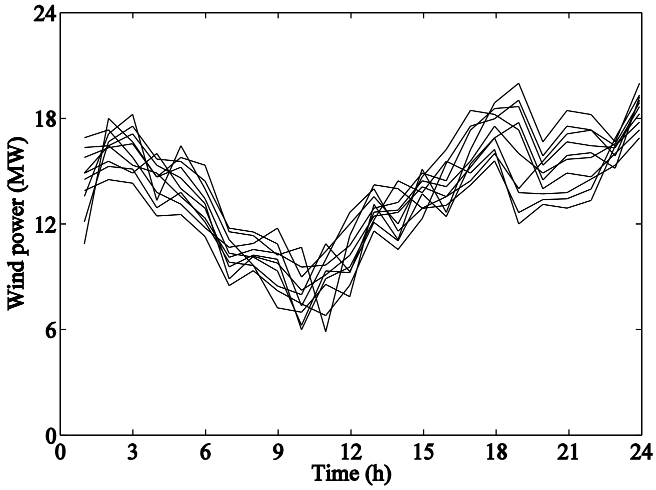

Fig. 5. Wind power scenarios considered in the case study.

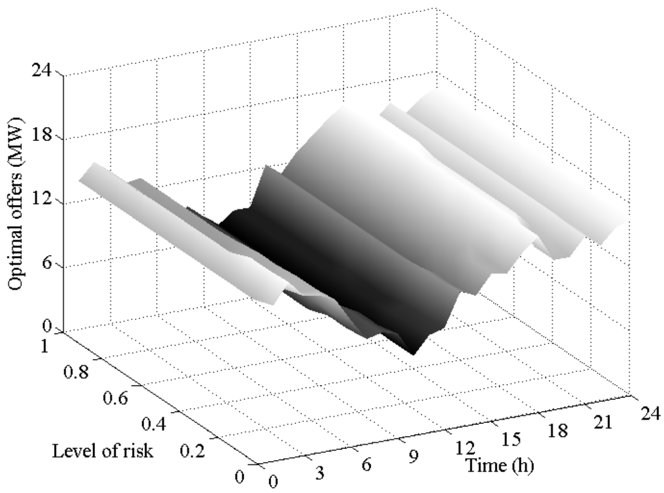

Fig. 6. Optimal hourly bids for different risk levels.

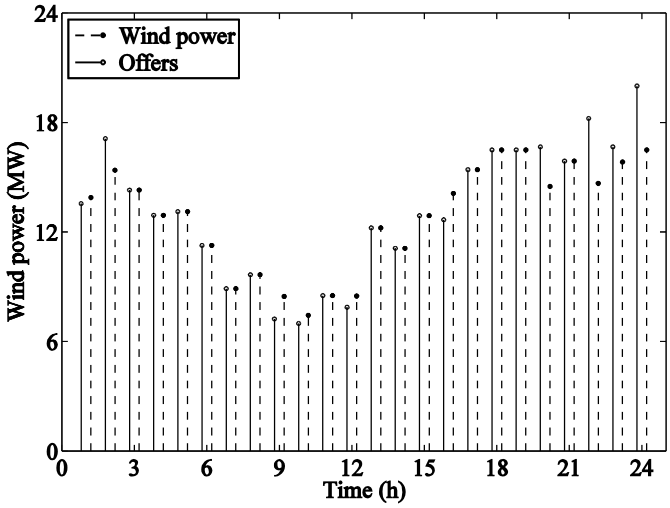

Fig. 7. Optimal offers to be submitted to the day-ahead market, and wind power production, for a risk level corresponding to $\beta = 1$.

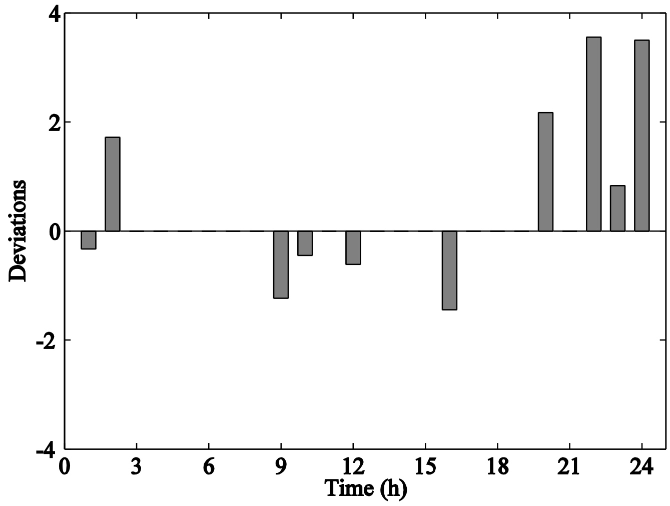

Fig. 8. Deviations resulting from the difference between the offers and the wind power production for a risk level corresponding to $\beta = 1$.

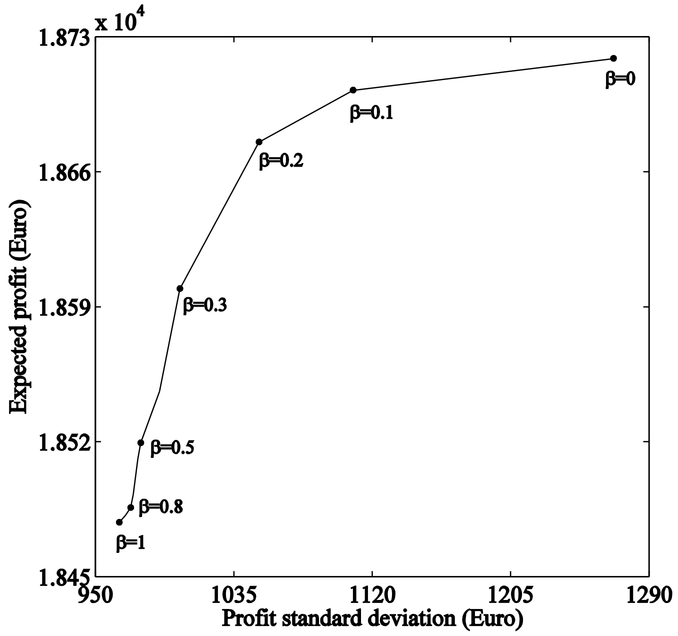

Fig. 9. Expected profit versus profit standard deviation.

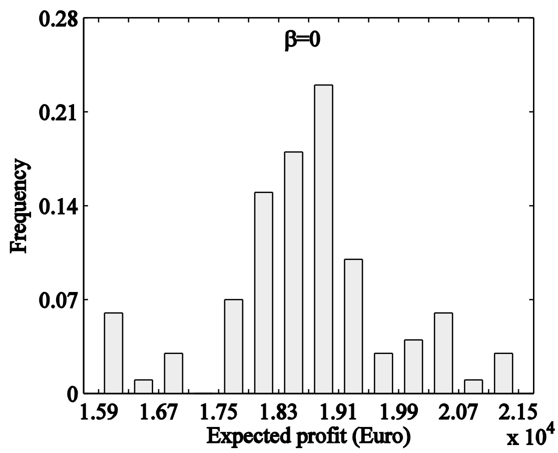

Fig. 10. Histogram of the profits for the risk level corresponding to $\beta = 0$.

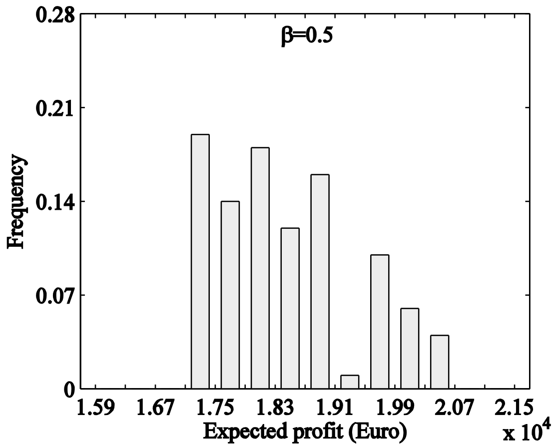

Fig. 11. Histogram of the obtained profits for the risk level corresponding to β = 0.5.

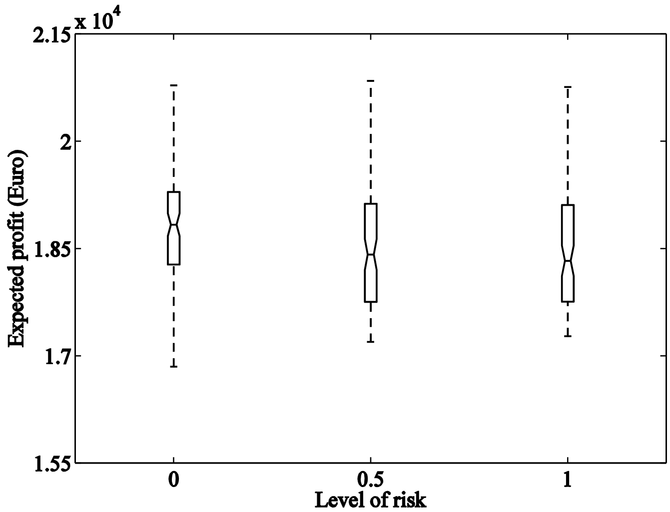

Fig. 12. Dispersion of profit for different risk levels.

Tables

Table 1

Scenarios considered, number and probability

	Number of scenarios	Probability
Energy price scenarios	10	0.10
Wind power scenarios	10	0.10
Imbalance price ratio scenarios	10	0.10
Total scenarios	1000	0.001

Table 2

Comparison of the increase in profit for several risk levels

Risk level	Profit standard deviation (€)	Expected Profit (€)	% Increase	CPU Time (s)
1.0	965	18478	-	1.62
0.9	969	18482	0.02	1.09
0.8	971	18486	0.04	1.05
0.7	973	18493	0.08	1.03
0.6	976	18511	0.18	1.01
0.5	978	18519	0.22	0.98
0.4	989	18546	0.37	0.96
0.3	1001	18599	0.65	0.92
0.2	1050	18675	1.07	0.88
0.1	1108	18702	1.21	0.82
0.0	1268	18719	1.30	0.76

Table 3

Confidence intervals

Risk Level	Confidence interval of 95% regarding the expected profit
0	[18509 ; 19016]
0.5	[18399 ; 18787]
1	[18368; 18754]