DEVELOPMENT OF RISK-CONSTRAINED OFFERING STRATEGIES FOR A WIND POWER PRODUCER UNDER UNCERTAINTY

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Abstract – Under a market framework, the development of optimal offering strategies is crucial for wind power producers to achieve maximum profit. In this paper, a two-stage stochastic programming approach is proposed, considering the uncertainties on wind power production and electricity market prices. An artificial intelligence model allows generating wind-price scenarios. Also, risk management is appropriately addressed. Results from a real-world case study are presented, in order to illustrate the proficiency of the proposed approach. Finally, conclusions are duly drawn.

Keywords: Generation, Wind energy, Risk, Uncertainty, Simulation

1 INTRODUCTION

Wind generation levels are growing in power systems around the world in response to increased pressure to reduce CO_2 levels and dependence on fossil fuels [1]. A high penetration of wind power into the electric grid is taking place, in countries such as Denmark, Spain, and Portugal. Unlike hydro or thermal systems [2], which are traditional dispatchable power sources, wind power is undispatchable [3] 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 wind power producers to achieve maximum profit.

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

To consider the uncertainties on wind power production and electricity market prices requires stochastic programming. Hence, a two-stage stochastic programming approach is proposed, dividing the set of decisions inherent to the problem into two distinct stages.

The aforementioned uncertainties were handled in [4] through traditional time-series models. Instead, an artificial intelligence model is considered in this paper to generate wind-price scenarios.

Risk management is also incorporated in the proposed stochastic programming approach, as in [4], by limiting the volatility of the expected profit through the conditional value-at-risk (CVaR) methodology [5].

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. Imbalance penalties are imposed to prevent gaming and to secure better system operation.

The experience with the implementation of the proposed two-stage stochastic programming approach on a realistic case study, based on a wind farm in Portugal, is reported. Finally, conclusions are duly drawn.

2 PROBLEM FORMULATION

2.1 Risk Management

CVaR represents an appropriate approach to address the integrated risk management problem of a wind power producer. Previous approaches [6]-[8] did not consider risk management.

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

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

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 $1-\alpha$:

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

The value of α is commonly set between 0.90 and 0.99 [9]. In this paper, α is considered equal to 0.95, as in [4]-[5].

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:

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

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

The concept of CVaR is illustrated in Figure 1.

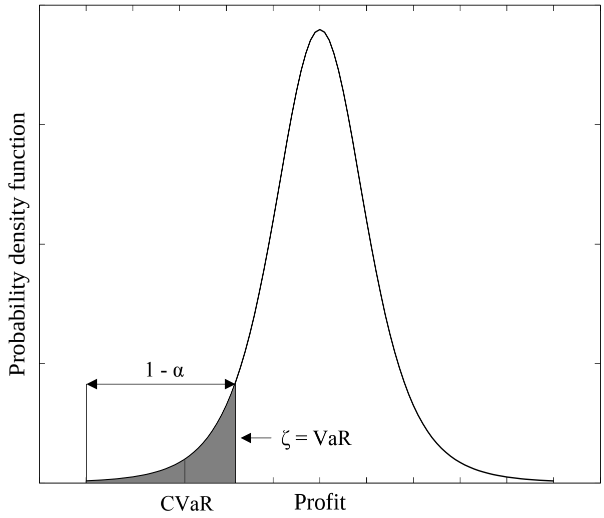

Figure 1: VaR and CVaR illustration.

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.

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.

2.2 Objective Function

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

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

The objective function (6) to be maximized includes the expected profit, the operational costs, and the CVaR of the profit, where S is the set of scenarios, ρ_s is the probability of occurrence of scenario *s*, H is the set of hours in the time horizon, λ_{sh} is the forecasted electricity market price in scenario *s* in period *h*, p_{sh} is the power output of the wind farm in scenario *s* in period *h*, $Pdev_{sh}$ is the penalization for deviation of the wind farm in scenario *s* in period *h*, b_{ih} is the operational cost associated to wind turbine *i* at period *h*, g_{ih} is the power output of the wind turbine *i* in period *h*, and β is the weighting parameter to achieve an appropriate tradeoff between profit and risk.

The deviations are measured in absolute value, and can be generated by excess or deficit of energy:

$$dev_{sh} = \left| p_{sh} - x_h \right| \quad (7)$$

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

$$Pdev_{sh} = \begin{cases} \lambda_{\mathrm{sh}}\, r_{sh}^{+}\, dev_{sh}, & dev_{sh} \geq 0 \\ \lambda_{\mathrm{sh}}\, r_{sh}^{-}\, dev_{sh}, & dev_{sh} < 0 \end{cases} \quad (8)$$

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

$$L_{sh} = \lambda_{sh}\, p_{sh} \quad (9)$$

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:

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

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 $r_{sh}^{+} \leq 1$ and $r_{sh}^{-} \geq 1$:

$$p_{sh} - x_h - d_{sh}^{+} + d_{sh}^{-} = 0 \quad (11)$$

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:

$$0 \leq d_{sh}^{+} \leq W_{sh} \quad (12)$$

$$0 \leq d_{sh}^{-} \leq P^{\max} \quad (13)$$

where W_{sh} is the forecasted wind power production in scenario *s* in period *h*, and $P^{\max}$ is the maximum power installed in the wind farm. Constraints (12) and (13) impose caps on the positive and negative deviations, respectively.

In (14), the offers are also limited by the maximum power installed in the wind farm:

$$0 \leq x_h \leq P^{\max} \quad (14)$$

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

$$x_h \leq \sum_{i=1}^{I} g_{ih} \quad (15)$$

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:

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

$$+\zeta-\eta_{s}\leq 0 \quad (16)$$

$$\eta_{s}\geq 0 \quad (17)$$

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:

$$\text{Max}\;\; F=c^{\mathrm{T}}x-\left|\,x\,\right| \quad (18)$$

subject to:

$$x^{\min}\leq x\leq x^{\max} \quad (19)$$

$$x\in \mathrm{R}^{\mathrm{n}} \quad (20)$$

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:

$$\left|\,x\,\right|=x^{+}+x^{-} \quad (21)$$

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

$$x=x^{+}-x^{-} \quad (22)$$

The equivalent linear programming problem is given by:

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

subject to:

$$x^{\min}\leq x\leq x^{\max} \quad (24)$$

$$x=x^{+}-x^{-} \quad (25)$$

$$x^{+}\geq 0,\quad x^{-}\geq 0 \quad (26)$$

3 PROPOSED APPROACH

3.1 Uncertainty Characterization

Uncertainties of wind power production and electricity market prices are handled by treating them as stochastic variables.

To generate wind-price scenarios, time-series models, such as ARIMA [4], or artificial intelligence models, such as neural networks [10], data mining and evolutionary computation [11], 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 wind power production and electricity market prices over the day. The WT convert the 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 step-by-step algorithm used to implement the hybrid intelligent approach can be seen in [12].

3.2 Scenario Tree

A scenario tree that is used to represent the first- and second-stage decisions is shown in Figure 2.

For the sake of problem tractability it may be convenient to reduce the size of the 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 [13].

3.3 Two-Stage Stochastic Programming Approach

The two-stage stochastic programming approach can be formulated as:

$$\text{Max}\quad c^{\mathrm{T}}x+E[\max\nolimits_{y_{\omega}}\, q_{\omega}^{\mathrm{T}}\; y_{\omega}] \quad (27)$$

subject to:

$$b^{\min}\leq Ax\leq b^{\max} \quad (28)$$

$$h_{\omega}^{\min}\leq T_{\omega}\; x+W_{\omega}\; y_{\omega}\leq h_{\omega}^{\max} \quad (29)$$

$$x\geq 0,\quad y_{\omega}\geq 0 \quad (30)$$

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.

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.

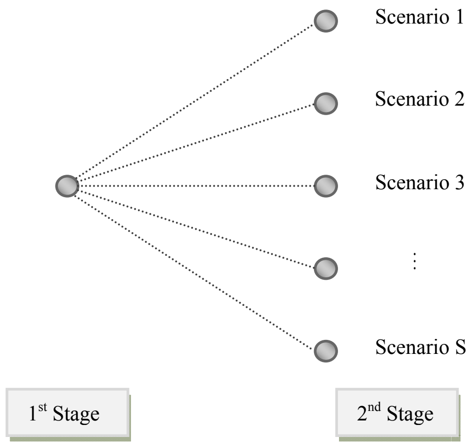

Figure 2: Scenario tree.

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:

$$\mathrm{Max}_{x,y_s} \quad c^{T} x + \sum_{s=1}^{S} \rho_s q_s^{T} y_s \tag{31}$$

subject to:

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

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

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

4 CASE STUDY

The proposed stochastic programming approach has been applied on a realistic case study, based on a wind farm in Portugal 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 RAM.

4.1 Input Data

The proposed approach takes into account the uncertainty in both wind power production and electricity 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 [14].

The time horizon chosen is one day divided into 24 hourly periods. This case study is composed of ten wind power production scenarios, Figure 3, and ten electricity market prices scenarios, Figure 4. The number of scenarios, although arbitrarily selected, adequately describes the stochastic processes. 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 $1/S$.

4.2 Results Analysis

A thorough comparison of the optimal offering strategies in the market for different risk levels using the proposed approach is presented thereafter.

The solution of the optimization model contains the optimal bids for the daily market. The optimal bids, shown in Figure 5, are common to the 1000 scenarios.

The two-stage stochastic programming approach contains $(H \cdot (3 \times S + I + 1) + S + 1)$ continuous variables and $(H \cdot (S + 1) + S)$ constraints. Hence, the problem size depends on the number of scenarios considered.

Figure 5 shows the ability of the wind power producer to trade in the day-ahead market taking into account the desired risk level.

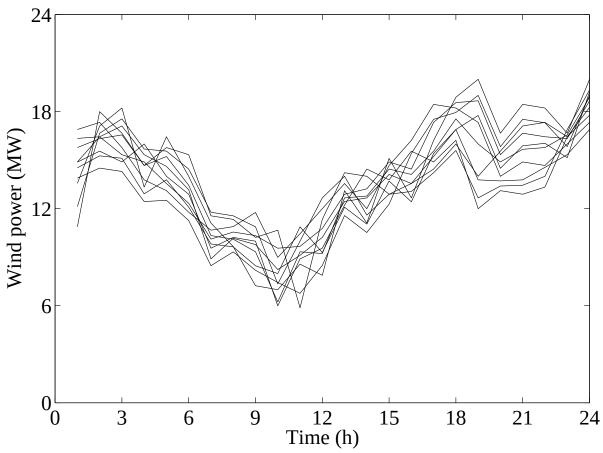

Figure 3: Wind power production scenarios.

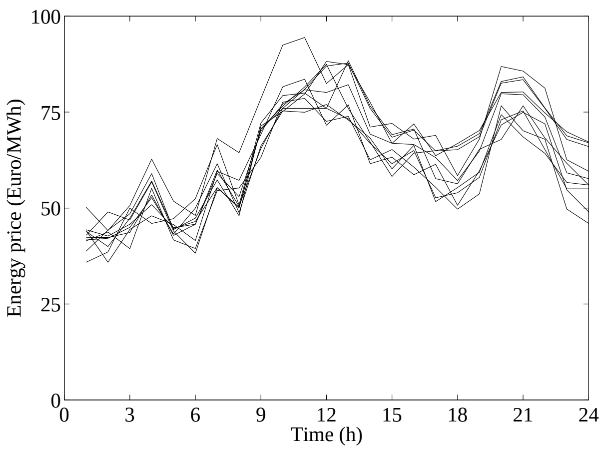

Figure 4: Electricity market price scenarios.

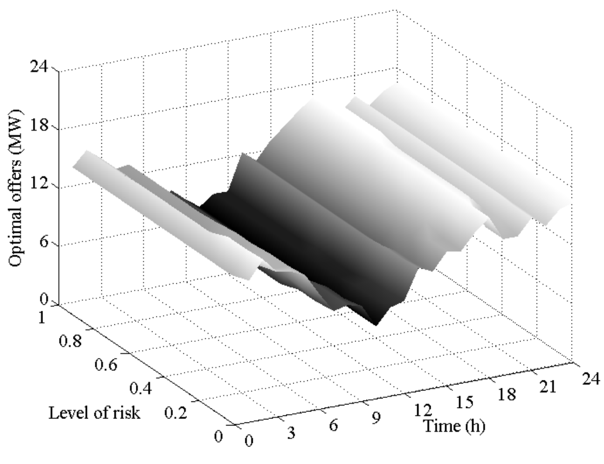

Figure 5: Optimal hourly bids for different risk levels.

Choosing one scenario of the problem, it can be verified in Figure 6 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 Figure 7. A positive deviation means that the wind power production was higher than the offer submitted to the day-ahead market, and vice-versa.

The expected profit versus profit standard deviation is presented in Figure 8, considering seven values for β and $\alpha = 0.95$ in all instances.

Figure 8 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 or Markowitz 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 €. Table 1 establishes a numerical comparison of the increase in profit for several risk levels.

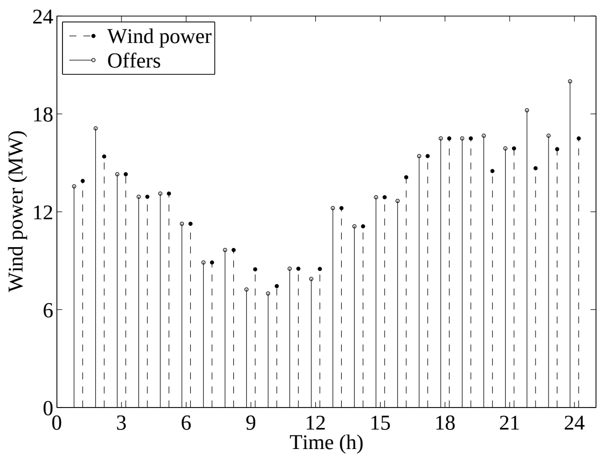

Figure 6: Optimal offers to be submitted to the day-ahead market, and wind power production, for a risk level corresponding to $\beta = 1$.

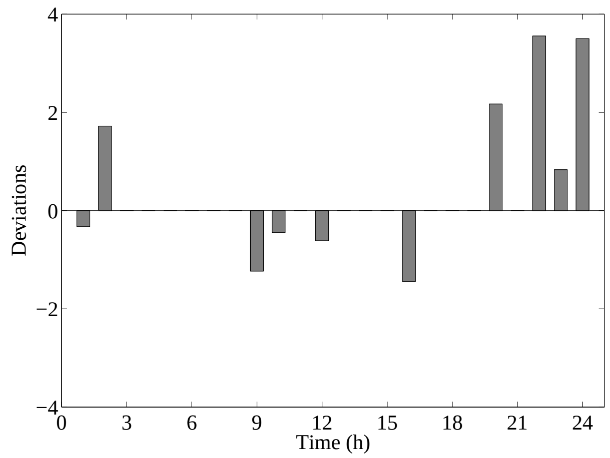

Figure 7: Deviations resulting from the difference between the offers and the wind power production for a risk level corresponding to $\beta = 1$.

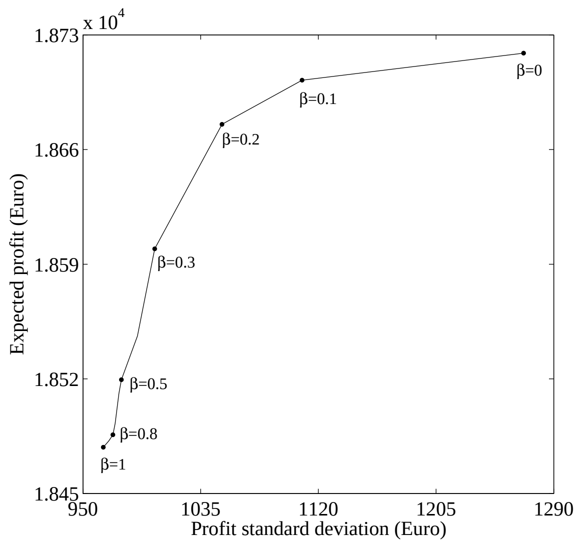

Figure 8: Expected profit versus profit standard deviation.

Risk Level	Profit Std. Deviation (€)	Expected Profit (€)	% Increase	CPU Time (s)
1.0	965	18478	-	1.62
0.8	971	18486	0.04	1.05
0.5	978	18519	0.22	0.98
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 1: 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 $\beta = 0$.

Figures 9 and 10 present the histograms of the profits for $\beta = 0$ and $\beta = 0.5$, respectively.

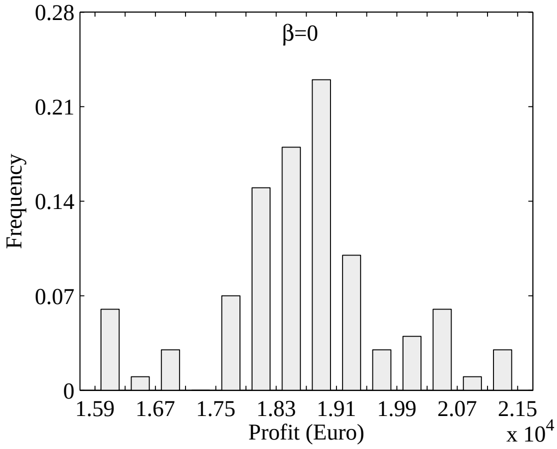

Figure 9: Histogram of the profits for the risk level corresponding to $\beta = 0$.

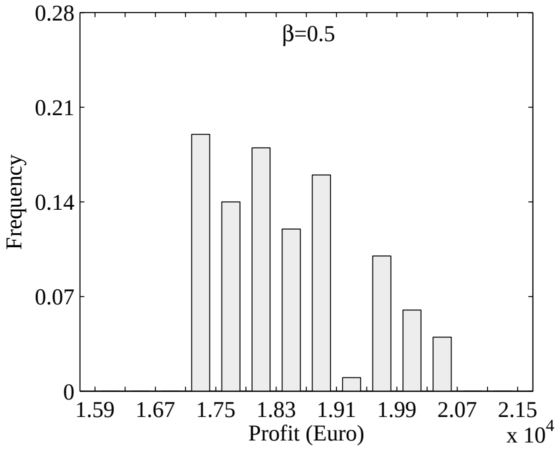

Figure 10: Histogram of the profits for the risk level corresponding to $\beta = 0.5$.

Analyzing Figures 9 and 10, it can be verified that the risk level corresponding to $\beta = 0$ implies a higher expected profit than for $\beta = 0.5$. Nevertheless, $\beta = 0$ is riskier than $\beta = 0.5$ because financial loss can occur under some scenarios, thus a risk-averse producer may prefer $\beta = 0.5$. Hence, our approach allows selecting the best solution according to the desired risk exposure level.

5 CONCLUSION

A two-stage stochastic programming approach is proposed in this paper to develop risk-constrained offering strategies for a wind power producer. Uncertainty is related to wind power production and electricity market prices. A hybrid intelligent approach generates wind-price scenarios, and risk management 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. Hence, the presented results on a realistic case study validate the proficiency of the proposed approach, enabling the selection of the best solution according to the desired risk exposure level, while the average computation time is acceptable.

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