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Investigation on the Development of Bidding Strategies for a Wind Farm Owner

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Abstract – *In this paper, the development of bidding strategies is investigated for a wind farm owner. The optimization model is characterized by making the analysis of scenarios. The proposed approach allows evaluating alternative production strategies in order to submit bids to the electricity market with the goal of maximizing profits. The problem is formulated as a linear programming problem. An application to a case study is presented.* ***Copyright © 2010 Praise Worthy Prize S.r.l. - All rights reserved.***

Keywords*: Bidding Strategies, Profit, Scenarios, Wind Power*

Nomenclature

S, s	Set and index of scenarios
H, h	Set and index of hours in the time horizon
ρ_s	Probability of occurrence of scenario s
λ_{sh}	Expected market price in scenario s in hour h
p_{sh}	Power output of the wind farm in scenario s in hour h
ν	Penalty factor over the market price for energy imbalances
x_h	Energy offered by the wind power producer in the day-ahead market for time hour h
ω_{sh}	Cost of penalization for deviation in scenario s in hour h
dev_{sh}	Deviation for wind production in scenario s in hour h
$Pdev_{sh}$	Penalization for deviation of the wind farm in scenario s in hour h
W_{sh}	Wind generation forecast in scenario s in hour h
p^{max}	Maximum power of the wind farm
L_{sh}	Revenue in scenario s in hour h
$\boldsymbol{c}$	Vector of coefficients for the linear term for first-stage
$\boldsymbol{x}$	Vector of decision variables
$\boldsymbol{A}$	Matrix of coefficients for the first-stage constraints
$\boldsymbol{b}^{min}$	Lower bound vector for the first-stage constraints
$\boldsymbol{b}^{max}$	Upper bound vector for the first-stage constraints
$\boldsymbol{x}^{min}$	Lower bound vector on variables
$\boldsymbol{x}^{max}$	Upper bound vector on variables
$\boldsymbol{h}_{\omega}^{min}$	Lower bound vector for the second-stage constraints
$\boldsymbol{h}_{\omega}^{max}$	Upper bound vector for the second-stage constraints
$\boldsymbol{T}_{\omega}$	Technology matrix.
$\boldsymbol{W}_{\omega}$	Recourse matrix
$\boldsymbol{q}_{\omega}$	Vector of coefficients for the linear term for the second-stage variables
$\boldsymbol{y}_{\omega}$	Second-stage variables that represent decisions to be made after part of uncertainty is revealed

I. Introduction

In nowadays, the renewable resources such as wind power [1], [2] play a significant role in electricity production, since they produce clean energy, respecting the compromise established by Kyoto protocol [3].

Since the implementation of this compromise, whose goal is to reduce CO_2 emissions to preserve a functioning atmosphere [4], that the governments of countries joined the European Union has clearly bet on the construction of infrastructure for the production of clean energy. These infrastructures consist in construction of wind farms, reducing the dependence on exogenous resources.

Portugal is a country of the European Union that has highlighted this area of energy innovation, giving a strong stimulus to the national economy by creating new jobs and scientific development based on the area of electrical power systems. In Portugal, the wind power goal foreseen for 2010 was established by the government as 3750 MW, representing about 25% of the total installed capacity in 2010 [5]-[7].

Due to the increase of wind power expansion in the next years many individual wind power markets need tools, which reduce the volatile effects associated to wind power and electricity prices, to help producers to submit their bids in the day-ahead market.

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So, this problem faced by many countries in Europe represents a challenging and evolving competitive environment.

Utility strategies are evolving towards greater European competition as mega utilities comply with renewable obligations and others look to build competitive advantage.

In deregulated markets, wind producers are entities owning generation resources and participating in the market with the goal of maximizing profits.

However, the challenges for wind producers are due to the uncertainty of wind power and electricity prices. For wind producers, large variability of wind power means a large variability in profit [8]. Thus the decision makers have to consider two kinds of uncertainty, as well as technical constraints associated to wind farms in operations.

In a competitive framework, producers require short-term wind power and electricity prices prediction to derive their bidding strategies to the electricity market. Short-term wind power forecasting is an extremely important field of research for the energy sector, as the system operators must handle an important amount of fluctuating power from the increasing installed wind power capacity [9].

The bid decisions to submit for electricity market have to be done in each hour, without knowing exactly what will be the value of power generation.

The differences between the produced energy and supplied energy constitute the energy imbalances. The imbalances should be penalized by the market balance [10], [11].

Hence, wind producers need to know how much to produce to make a realistic bid, because in case to error for excess or defect bids, other producers must reduce or increase production to fill the so-called deviation, causing economic losses.

These economic losses are reflected in so-called penalties for deviation.

To take into account these uncertain measures, wind power and electricity price forecasting, multiple scenarios can be used. Thus, the stochastic nature of these measures is modeled through two-stage stochastic programming approach [4], [12]-[15].

In this approach, the set of decisions inherent to this problem can be divided into two distinct stages:

- First-stage decisions, must be taken before resolving the uncertainty. The only significant decisions are those of the first stage, since only they are taken immediately.
- Second-stage decisions, are made after the uncertainty occurs and are influenced by the decisions taken in the first stage.

Hence, the first-stage decisions are the hourly bids to be submitted to the day-ahead market, and the second-stage decisions are related to the power output of the wind farm in each hour of a given scenario.

A scenario tree represents the different stages that can take the random parameters, i.e., different realizations of uncertainty.

The tree is a natural and explicit way of representing nonanticipativity decisions. The node or root of the tree represents the decision variables of the first stage, which in this case are the bids to submit to the daily market. These decisions are shared, that is, are the same for all scenarios since they are independent of them.

The second-stage decisions, which correspond to the production of wind depending on each scenario.

Fig. 1 shows the scenarios tree that will be used to represent the decisions to be taken in the two stages mentioned.

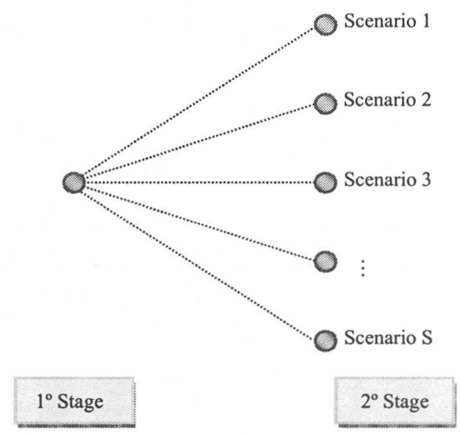

Fig. 1. Scenario tree

This paper is structured as follows. Section II presents the problem formulation. Section III provides the proposed approach. Section IV presents the case study. Finally, Section V outlines the conclusions.

II. Problem Formulation

The goal of the optimization problem described below is intended to provide the values of the following variables:

- To provide the maximum profit;
- To provide the optimal bids that should be submitted to the day-ahead market;
- Wind power generated;
- Value of wind power shifted every hour;
- Penalty for economic deviations of the wind farm.

II.1. Objective Function

In this paper, the objective function is defined as the sum in each of the scenarios considered by the profit of the wind farm, multiplied by the probability of each scenario. The profit of the wind farm is obtained by the difference between the revenue of the wind farm and the economic penalty caused by deviations.

Thus, the objective function to be maximized can be expressed as:

$$F = \sum_{s=1}^{S} \rho_s \sum_{h=1}^{H} [\lambda_{sh}\, p_{sh} - \nu\, \lambda_{sh}\, dev_{sh}] \tag{1}$$

The objective function represents the total profit on the sale of wind energy in each scenario, taking into account the probability of occurrence, less a penalty for deviations from the bids. The deviation in each hour is defined as the difference between the production of energy and the supply of production delivered to the network in a given period of time horizon.

The deviations are measured in absolute value, and can be generated by excess supply on the production or vice versa:

$$dev_{sh} = \begin{cases} p_{sh} - x_h, & p_{sh} - x_h \geq 0 \\ -p_{sh} + x_h, & p_{sh} - x_h < 0 \end{cases} \tag{2}$$

The cost of deviation is set as a percentage of the daily market price:

$$\omega_{sh} = \nu\, \lambda_{sh} \tag{3}$$

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

$$Pdev_{sh} = \omega_{sh}\, dev_{sh} \tag{4}$$

The revenue is given by the product delivered to the network by the daily market price:

$$L_{sh} = \lambda_{sh}\, p_{sh} \tag{5}$$

The profit of the operation was calculated as the difference between the profit of the wind farm and the cost of the gaps between production and supply:

$$F = L_{sh} - Pdev_{sh} \tag{6}$$

The objective function is obtained by substituting the equations (4) and (5) in equation (6), resulting in the following equation:

$$F = \sum_{s=1}^{S} \rho_s \sum_{h=1}^{H} [\lambda_{sh}\, p_{sh} - \nu\, \lambda_{sh}\, |p_{sh} - x_h|] \tag{7}$$

II.2. Constraints

In order to make the bids to the market, it is required to satisfy the technical limitations 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:

$$0 \leq p_{sh} \leq W_{sh} \tag{8}$$

In inequality (8), wind power is limited superiorly by value of wind generation forecast.

The value of wind generation forecast is not always attainable due to intermittent wind:

$$0 \leq x_h \leq P^{max} \tag{9}$$

In inequality (9), the bids are limited by maximum power installed in the wind farm.

II.3. Linearization of Objective Function

The objective function, presented in the previous subsection, is characterized by nonlinearity due to the existence of the absolute value.

So, it is required to use a mathematical process that allows reformulating into a linear problem. In this subsection, we describe how the problem involving absolute value terms can be transformed into a standard linear programming formulation.

The first problem is to maximize:

$$Max\ \ F = \boldsymbol{c}^T \boldsymbol{x} - |\boldsymbol{x}| \tag{10}$$

subject to:

$$\boldsymbol{x}^{min} \leq \boldsymbol{x} \leq \boldsymbol{x}^{max} \tag{11}$$

$$\boldsymbol{x} \in R^n \tag{12}$$

In (10) is presented an objective function dependent of the decision variables.

The first step of reformulation problems with absolute values is to replace all absolute valued variables with two strictly positive variables with the substitution:

$$|\, \boldsymbol{x}\, | = \boldsymbol{x}^+ + \boldsymbol{x}^- \tag{13}$$

In addition to a direct substitution of each variable by the difference of the same two positive variables, as:

$$\boldsymbol{x} = \boldsymbol{x}^+ - \boldsymbol{x}^- \tag{14}$$

In general, the equivalent linear programming problem is to maximize:

$$Max\ \ F = \boldsymbol{c}^T \boldsymbol{x}\ - \left(\boldsymbol{x}^+ + \boldsymbol{x}^-\right) \tag{15}$$

subject to:

$$x^{min} \le x \le x^{max} \tag{16}$$

$$x = x^{+} - x^{-} \tag{17}$$

$$x^{+} \ge 0 \ , \ x^{-} \ge 0 \tag{18}$$

III. Proposed Approach

The stochastic programs are among the most challenging optimization problems [16]. The stochasticity in the parameters appears in this approach due to uncertainty, modeled via a finite set of scenarios. A theoretical treatment of the approach is provided to prove that the approach obtains the optimal solution.

III.1. Two-stage Stochastic Programming

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

$$Max \quad c^{T} x + E\left[max_{y_{\omega}} \, q_{\omega}^{T} \, y_{\omega} \right] \tag{19}$$

subject to:

$$b^{min} \le Ax \le b^{max} \tag{20}$$

$$h_{\omega}^{min} \le T_{\omega} \, x + W_{\omega} y_{\omega} \ \le h_{\omega}^{max} \tag{21}$$

$$x \ge 0, \quad y_{\omega} \ge 0 \tag{22}$$

In the first-stage, the "here-and-now" 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 value of 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.

III.2. Deterministic Equivalent Programming

The stochastic model is usually a difficult computational problem, so 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 previous subsection is equivalent to the so-called deterministic equivalent programming that in the splitting variable representation is as follows:

$$Max_{x,y_s} \quad c^{T} x + \sum_{s=1}^{S} \rho_s q_s^{T} y_s \tag{23}$$

subject to:

$$b^{min} \le Ax \le b^{max} \tag{24}$$

$$h_s^{min} \le T_s \, x + W_s \, y_s \ \le h_s^{max} \tag{25}$$

$$x \ge 0, \quad y_s \ge 0 \tag{26}$$

The matrix composed by (24) and (25), for linear problems with large scale can be generally represented according with Fig. 2.

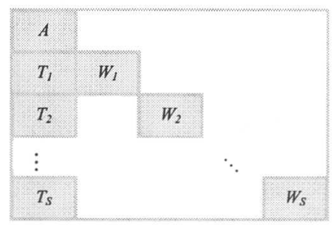

Fig. 2. Layout of the constraints associated with two stages

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 2GB of RAM. The proposed approach has been applied on a case study based on a Portuguese wind farm. The total installed wind power capacity of the plant is 265 MW.

The deregulation of the electricity markets brings uncertainty to electricity prices. A good forecasting tool provides a risk hedging mechanism for generating companies against price volatility [17]. In addition, a generating company can develop an appropriate bidding strategy to maximize its own profit with an accurate price forecast, which represents an advantage facing competition.

The time horizon chosen is one day divided into 24 hourly periods. This case study is composed of four electricity price scenarios computed by the approach proposed in [18], Fig. 3, and four wind power scenarios computed by the approach proposed in [8], Fig. 4, over the time horizon.

The number of scenarios generated for the day-ahead market in the optimization problem is N = 16. This number has been arbitrarily selected, and the probability of each generated scenario will be $1/N$.

It can be seen in Fig. 5 that the wind farm owner adjusts its production to minimize deviations, but in almost every hour there are small differences between the bids and power output of the wind farm.

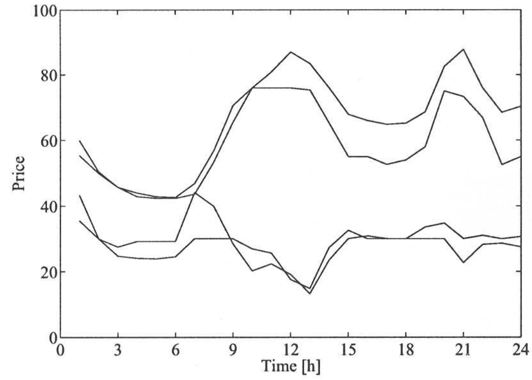

Fig. 3. Prices scenarios considered in the case study

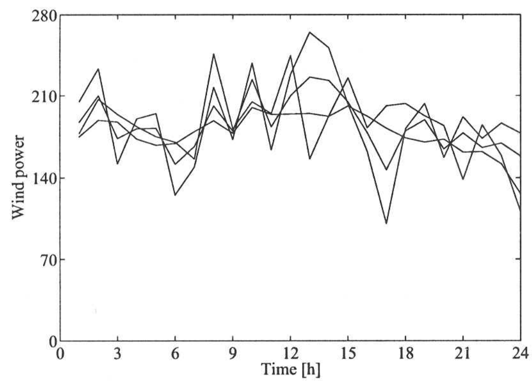

Fig. 4. Wind power scenarios considered in the case study

Table I summarizes the data of the scenarios that compose the probability tree.

TABLE I
SCENARIOS CONSIDERED: NUMBER AND PROBABILITY

	Number of scenarios	Probability
Price scenarios	4	0.25
Wind scenarios	4	0.25
Total scenarios	16	0.0625

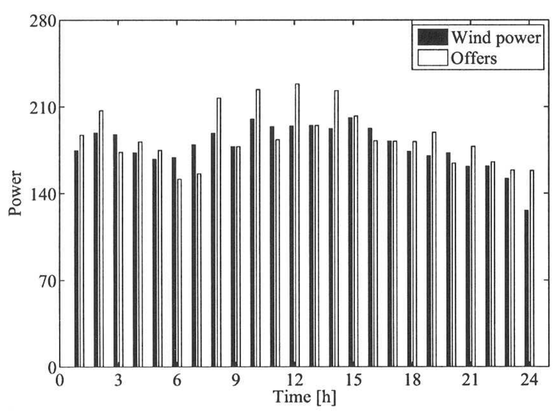

Fig. 5. Bids to be submitted to the day-ahead market and power produced

The wind power problem are the deviations that are generated between the actual wind power production and the production sold to the market due to intermittent nature of wind, which prevents to know with certainty what will be the production for the next day after issuing offers to the day-ahead market. The deviations from generated power for this scenario are shown in Fig. 6.

The total profit obtained for the day of operation analyzed using a stochastic programming approach is $196 597.

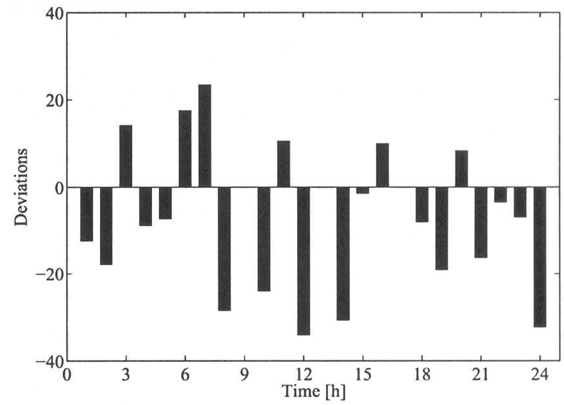

Fig. 6. Deviations resulting from the difference between the offers and the power produced

V. Conclusion

The new environment of competitive electricity markets for energy requires new computing tools to allow generating companies to achieve better bidding strategies. In this paper, the goal is to maximize the profit of a wind farm owner, reducing deviations, and taking into account the uncertainty associated with wind energy production and electricity prices. The case study is composed of four electricity price scenarios and four wind power scenarios, over the time horizon. Considering the proposed stochastic programming approach, the wind farm owner adjusts its production to minimize deviations, but in almost every hour there are small differences between the bids and power output of the wind farm.

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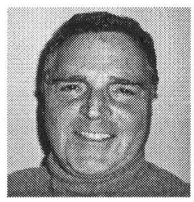

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