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Abstract. This paper presents a stochastic optimization-based approach applied to offer strategies of a wind power producer in a day-ahead electricity market. Further from facing the uncertainty on the wind power the market forces wind power producers to face the uncertainty of the market-clearing electricity price. Also, the producer faces penalties in case of being unable to fulfill the offer. An efficient mixed-integer linear program is presented to develop the offering strategies, having as a goal the maximization of profit. A case study with data from the Iberian Electricity Market is presented and results are discussed to show the effectiveness of the proposed approach.

Keywords: Mixed-integer linear programming; stochastic optimization; wind power; offering strategies.

1 Introduction

Renewable energy sources are viewed as of crucial usage for a sustainable society development [1] and the industry of conversion into electric energy is already exploiting these sources. Renewable energy sources can partly replace fossil fuel sources, avowing carbon emissions and reducing the fuel-import dependency on countries with rich fossil fuel stocks. Countries promote the usage of renewable energy sources by supporting mechanisms and policies to provide incentive or subsidy for renewable energy capturing [2]. Nowadays wind power is integrated into the electric power grid and there are encouragements by extra-market actions, involving, for instances, legislation, directives, feed-in tariffs, encouraging penalty pricing and guaranteed electric grid access [3]. These actions runs at modest penetration levels in nowadays, but will become flawed as wind power penetration increases [3]. This will force wind power producers (WPPs) to face the challenges of a day-ahead electricity market and bilateral contracting. For instance: in Portugal, WPPs are rewarded with a feed-in tariff in conditions of a limited amount of time or energy delivered, if one of these conditions fails, energy is sold either in the day-ahead electricity market or by bilateral contracts [4]; in United Kingdom, large WPPs are forced to participate in whole-sales markets and subjected to financial penalties in case of deviation from contracts in forward markets [5]. Intermittency and variability of wind power are WPP concerns of uncertainty in what regards imbalance penalties due to imbalance on the electric power delivered [6]. This paper is a contribution to deal with these concerns of uncertainty by using an approach based on stochastic optimization MILP to enable WPPs to optimize their offers having as a goal the maximization of profit in a day-ahead electricity market.

2 Relationship to Cloud-based Solutions

Cloud-based solutions can help the processing of approaches for helping trading in a day-ahead electricity market in order to take greater advantages of bids, requiring methodological approaches demanding computational effort not currently available to the WPP. Among these approaches the ones for the solution of the problems concerning with energy management, unit commitment and energy offers are particular vital for upholding a WPP business. The approaches to solve these problems have been limited by the available computational resources, i.e., details concerning some reality are disregard in view of the excessive use of computational requirements. These limitations are evident for large systems and lead to solutions not conveniently addressed in agreement with the reality, because the computational resources do not allow the usage of data or modeling for delivering more adequate solutions. Particularly, in what regards the fact that for WPP the market brings uncertainty and paying penalties due to uncertainty on wind power exploitation: the stochastic concern with scenarios data implies the processing of large sets of data requiring the use of reduction techniques to avoid the use of significant computational requirements.

Cloud-based solutions are able to contribute for upholding a WPP by setting out an adequate availability of computational resources needed to address those problems in due time. Although of the uncertainty on the wind power, i.e., intermittency and variability, cloud-based engineering systems will deal with problems approaching the full reality with gains in terms of profits for WPP's. Cloud-based solutions will help out smoothing the market-clearing electricity price due to the fact of having bids of wind power with higher level of energy and with more certainty in what regards the satisfaction on delivering the electric power accepted at the market-closing. Also, environmental benefits are expected with the increment in the ability of finding offers able to be fulfilled with a high level of being satisfied, i.e., integrating renewable energy into the electric grid with less deviation from the assumed compromises: less spinning reserved is needed, less thermal units are needed and less fossil fuel is used. Eventually, cloud-based solutions will allow processing approaches in order that when at a WPP site the renewable energy is available is all captured to be converted in electric energy to be injected without concerns on dynamic stability into the electric grid in due time.

3 State of the Art

Wind power and the market-clearing electricity price uncertainties are passed on the variables of the problems [7,8] to be addressed by the WPP in order to know how much to produce in order to formulate realistic bids, because in case of excessive or moderate bids, other producers must reduce or increase production to fill the so-called deviation, implying penalties causing economic losses [1]. In order for upholding a WPP in a competitive environment, three main lines of action have been proposed in the technical literature: One of them is based on the use of wind power with energy storage technologies [9]–[11]; another one is the use of financial options as a tool for WPP to hedge against wind power uncertainty [12]; and the final one focuses on designing stochastic models intended to produce optimal offer strategies for WPP participating in an electricity market [13]–[15], without depending on third-parties or governmental regulations. The third line of action is a stochastic formulation explicitly modeling the uncertainties faced by the scheduling activities of a WPP [16], using uncertain measures and multiple scenarios built by wind power forecast [17]–[19] and market-clearing electricity price forecast [20]–[22] applications. Mixed integer linear programming (MILP) is one of the most successful explored methods for scheduling activities because of rigorousness, flexibility and extensive modeling capability [23]. Hence, MILP is expected to be also a successful method for solving WPP problems in the context of the day-head electricity market and this paper aims at show the usefulness of this method for WPPs.

4 Problem Formulation

Wind energy conversion into electric energy for trading in a day-head market involves facing up uncertainties that must be taken into account in devising of the offer strategy. The uncertainties are due to the intermittence and variability on the available wind power and due to the market-clearing electricity price. These uncertainties if not conveniently addressed are capable of losses on profit due to the incurred imbalance penalties. The problem formulation in this paper is an addressing in a convenient way.

System imbalance is defined as a non-null difference on the trading between the delivered energy and the offered energy. If there is an excess of delivered energy in the power system, the system imbalance is positive; otherwise, the system imbalance is negative. The system operator seeks to minimize the absolute value of the imbalance in a power system through a mechanism based on prices penalization for the deviation of the delivered energy from the one offered by a producer in the day-ahead market. If the system imbalance is negative, the system operator keeps the price for the energy in excess for the producers with excess of offers, and pays a premium price for the energy produced above the offer. The prices are as follow

$$\lambda_t^{+} = \lambda_t^{D} \tag{1}$$

$$\lambda_t^{-} = \max(\lambda_t^{D}, \lambda_t^{UP}) \tag{2}$$

In (1) and (2), λ_t^{+} and λ_t^{-}, are applied in the balancing market to the energy deviations, λ_t^{D} is the day-ahead market-clearing price and λ_t^{UP} is the price of the energy that needs to be added to the system. If the system imbalance is positive, the prices are as follow

$$\lambda_t^{+} = \min(\lambda_t^{D}, \lambda_t^{DN}) \tag{3}$$

$$\lambda_t^{-} = \lambda_t^{D} \tag{4}$$

In (3), λ_t^{DN} is the price of the energy of offers in exceeds. The uncertainties in the available wind power may result in differences between the energy offered by a WPP and the actual energy delivered. The revenue R_t of the WPP for hour t is as follows

$$R_t = \lambda_t^{D} P_t^{D} + I_t \tag{5}$$

In (5), P_t^{D} is the power traded by the WPP in the day-ahead market and I_t is the imbalance income resulting from the balancing penalty.
Since the total deviation for hour t is as follows

$$\Delta_t = P_t - P_t^{D} \tag{6}$$

where P_t is the actual power for hour t . I_t is given as follows

$$I_t = \lambda_t^{+} \Delta_t, \Delta_t \geq 0 \tag{7}$$

$$I_t = \lambda_t^{-} \Delta_t, \Delta_t < 0 \tag{8}$$

In (6), a positive deviation means the actual production is higher than the traded in the day-ahead market and a negative deviation means an actual production lower than the traded, this way λ_t^{+} is the price paid to the WPP for its excess of generation and λ_t^{-} the price to be charged for the deficit. Let

$$r_t^{+} = \frac{\lambda_t^{+}}{\lambda_t^{D}}, r_t^{+} \leq 1 \tag{9}$$

$$r_t^{-} = \frac{\lambda_t^{-}}{\lambda_t^{D}}, r_t^{-} \geq 1 \tag{10}$$

Then

$$I_t = \lambda_t^{D} r_t^{+} \varDelta_t, \varDelta_t \geq 0 \tag{11}$$

$$I_t = \lambda_t^{D} r_t^{-} \varDelta_t, \varDelta_t < 0 \tag{12}$$

A WPP that needs to correct the energy deviations in the balancing market incurs an opportunity cost because in the day-ahead market energy is traded at a more competitive price. Equation (5) can be rewritten to reflect the opportunity cost. Two cases have to be considered. If the energy deviation is positive, $\Delta_t > 0$, the revenue is given as follows

$$R_t = \lambda_t^D P_t^D + \lambda_t^D r_t^+ \Delta_t \qquad \textbf{(13)}$$

Using the total deviation expressed in equation (6), the revenue is given as follows

$$R_t = \lambda_t^D P_t^D - \lambda_t^D (1 - r_t^+) \Delta_t ,\ \Delta_t \geq 0 \qquad \textbf{(14)}$$

Similarly, if the energy deviation is negative, the revenue is given as follows

$$R_t = \lambda_t^D P_t^D + \lambda_t^D (r_t^- - 1) \Delta_t ,\ \Delta_t < 0 \qquad \textbf{(15)}$$

Equations (14) and (15) can be expressed in a general form as follows

$$R_t = \lambda_t^D P_t^D - C_t \qquad \textbf{(16)}$$

where

$$C_t = \lambda_t^D (1 - r_t^+) \Delta_t ,\ \Delta_t \geq 0 \qquad \textbf{(17)}$$

$$C_t = -\lambda_t^D (r_t^- - 1) \Delta_t ,\ \Delta_t < 0 \qquad \textbf{(18)}$$

In (16), the term $\lambda_t^D P_t^D$ is the maximum revenue that the WPP can collect from trading the energy in a situation without wind power uncertainty. With wind power uncertainty a set of scenarios Ω is considered for wind power and system imbalances. Each scenario ω is weighted with a probability of occurrence π. The expected optimal revenue of the WPP over a time horizon is obtained be the maximization of the objective function given as follows

$$\sum_{\omega=1}^{N_\Omega} \sum_{t=1}^{N_T} \pi_\omega \left(\lambda_{t\omega}^D P_t^D + \lambda_{t\omega}^D r_{t\omega}^+ \Delta_{t\omega}^+ - \lambda_{t\omega}^D r_{t\omega}^- \Delta_{t\omega}^- \right) \qquad \textbf{(19)}$$

The maximization is subjected to constraints as follow

$$0 \leq P_t^D \leq P^{\max}, \forall t \qquad \textbf{(20)}$$

$$\Delta_{t\omega} = \left(P_{t\omega} - P_t^D \right), \forall t, \forall \omega \qquad \textbf{(21)}$$

$$\Delta_{t\omega} = \Delta_{t\omega}^+ - \Delta_{t\omega}^-, \forall t, \forall \omega \qquad \textbf{(22)}$$

$$0 \leq \Delta_{t\omega}^+ \leq P_{t\omega}\, d_t ,\ \forall t, \forall \omega \qquad \textbf{(23)}$$

In (20) the limit of offers to the maximum power installed in the wind farm is set. In (21) to (23) is imposed $\Delta_{t\omega}^+ = 0$ when $\Delta_{t\omega}^+$ is negative, $P_{t\omega} < P_t^D$, and imposed $\Delta_{t\omega}^- = 0$ when $\Delta_{t\omega}^-$ is negative, $P_t^D < P_{t\omega}$. When the system balance is negative, the WPP is penalized for the deficit of energy generated below the energy traded in the day-ahead market, so the term $\lambda^D_{t\omega} r^+_{t\omega} \Delta^+_{t\omega}$ is null and the term $\lambda^D_{t\omega} r^-_{t\omega} \Delta^-_{t\omega}$ is subtracted from the revenue in the situation of no deviation, $\lambda^D_{t\omega} P^D_t$. When the system balance is positive, the WPP is penalized for the energy generated above the energy traded in the day-ahead market, so the term $\lambda^D_{t\omega} r^-_{t\omega} \Delta^-_{t\omega}$ is null and the term $\lambda^D_{t\omega} r^+_{t\omega} \Delta^+_{t\omega}$ is subtracted from the revenue in the situation of no deviation.

5 Case Study

The effectiveness of the proposed stochastic MILP approach is illustrated by a case study using two sets of data from the Iberian electricity market [24]. The first data set comprises 10 days of November 2013 and the second 10 days of June 2014 as are respectively shown in Fig. 1.

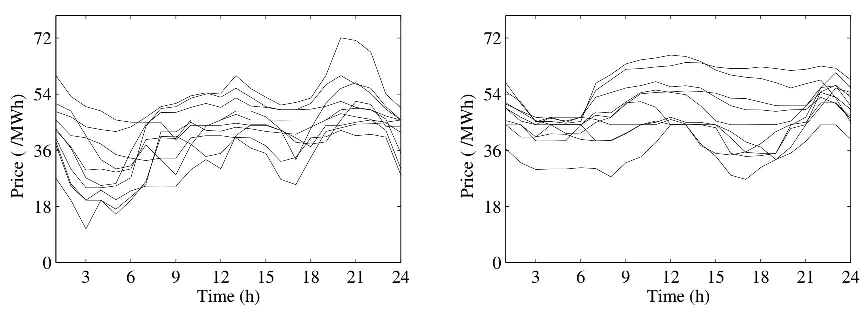

Fig 1. Price scenarios; left: November 2013, right: June 2014.

The total energy produced in 2013 and 2014 are respectively shown in Fig. 2.

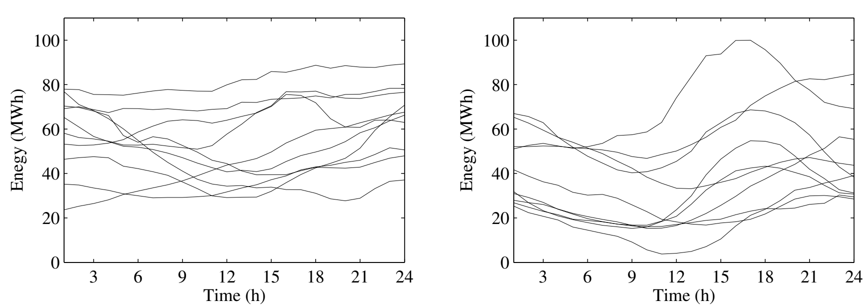

Fig 2. Energy from wind; left: November 2013, right: June 2014.

The energy produced is obtained using the total energy produced from wind scaled to the maximum power, $P^{\max} = 120MW$. The system operator matches the total energy production to the system needs. This is achieved by defining the price multipliers r_t^+ and r_t^- given by (9) and (10). The r_t^+ and r_t^- in 2013 are respectively shown in Fig. 3.

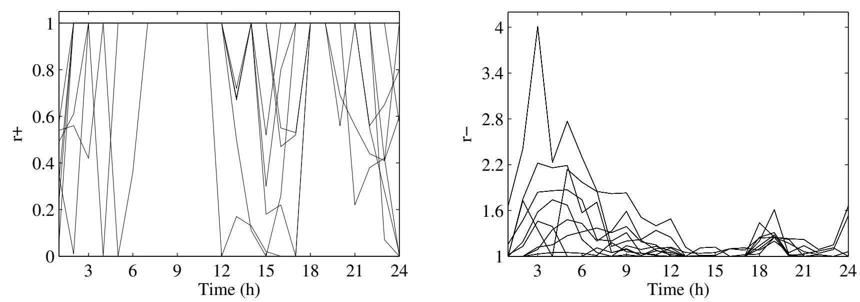

Fig 3. Imbalance price multipliers 2013; left: r_t^+, right: r_t^-.

The r_t^+ and r_t^- in 2014 are shown in Fig. 4.

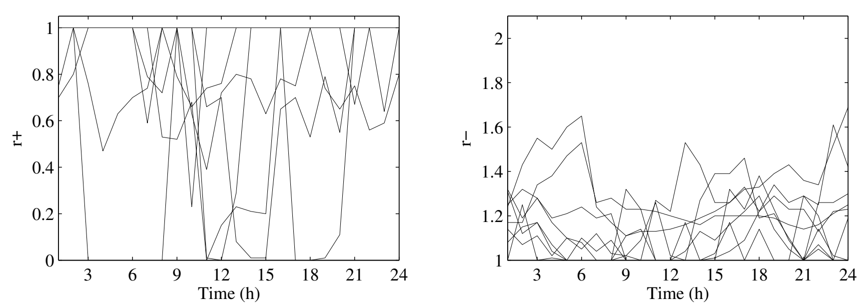

Fig 4. Imbalance price multipliers 2014; left: r_t^+, right: r_t^-.

The optimal energy offer in conditions of maximizing a WPP revenue is determined by (19) to (23). The optimal energy offer and the expected hourly revenue are respectively shown in Fig. 5 and Fig. 6.

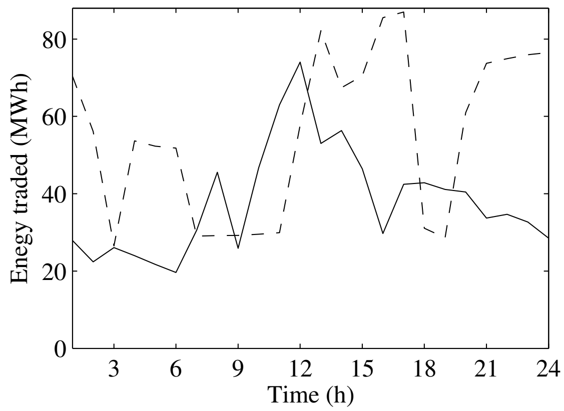

Fig 5. Energy traded day-ahead market; dashed-line: 2013, solid line: 2014.

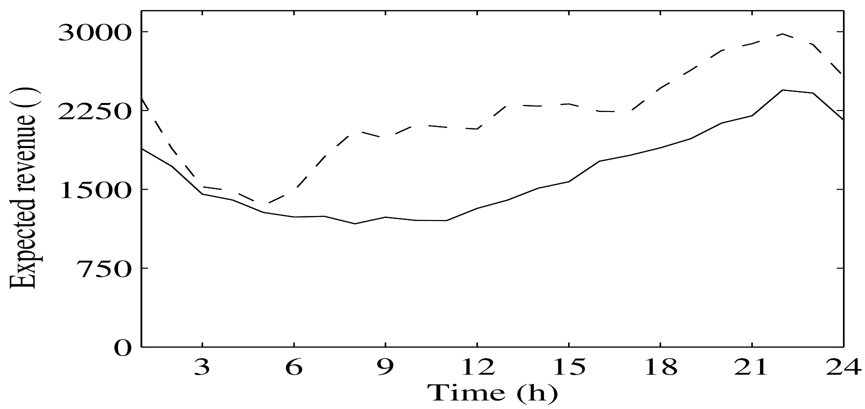

Fig 6. Expected hourly revenue; dashed-line: 2013, solid line: 2014

The forecasted revenue for the 24 hours is 52,861 € in 2013 and 39,656 € in 2014. The difference between the expected revenue and the revenue for each scenario, assuming that the 24 hours will behave exactly the same in each scenario is shown in Fig. 7

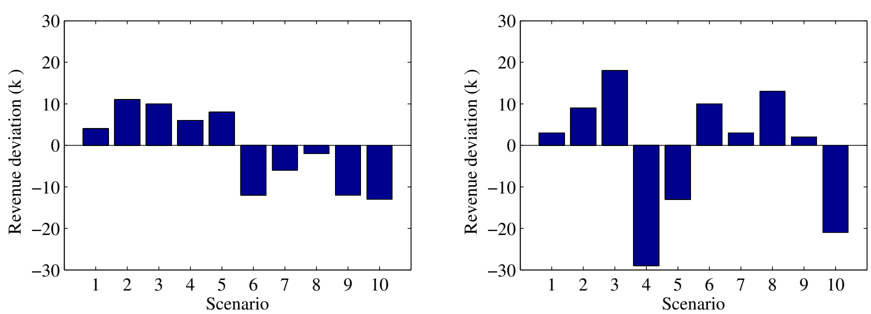

Fig 7. Revenue deviation; left: 2013, right: 2014.

In each year, the deviation for the worst case scenario is lower than the expected revenue, which means that if the condition during the day matches any one of the scenarios, the result would be always positive.

6 Conclusion

A stochastic MILP approach for solving the offering strategy of a WPP in a deregulated market is discussed in this paper and envisaged as potential convenient for the producers with the help of cloud-based solutions. The main result is the bidding strategy for a WPP facing the wind power and price uncertainties, as well the system imbalances which affect the price in case of deviations between the energy traded in the day-ahead market and the actual energy produced by the WPP.

Stochastic programming is a suitable approach to address parameter uncertainty in modeling via scenarios. The proposed stochastic MILP approach proved both to be accurate and computationally acceptable, since the computation time scales up linearly with number of price scenarios, units and hours over the time horizon. Since the bids in the pool-based electricity market are made one day before, this approach is a helpful tool for the decision-maker.

References

1. Pousinho, H.M.I., Catalão, J.P.S., Mendes, V.M.F.: Offering strategies for a wind power producer considering uncertainty through a stochastic model. Proceedings of PMAPS 2012 (2012)
2. Kongnam, C., Nuchprayoon, S.: Feed-in tariff scheme for promoting wind energy generation. IEEE Bucharest Power Tech Conference (2009)
3. Bitar, E.Y., Poolla, K.: Selling wind power in electricity markets: the status today, the opportunities tomorrow. 2012 American Control Conference June 27-June 29, Canada (2012)
4. Barros, J., Leite, H.: Feed-in tariffs for wind energy in Portugal: current status and prospective future. Electrical Power Quality and Utilisation (EPQU) (2011)
5. Barros, J., Leite, H.: Feed-in tariffs for wind energy in Portugal: current status and prospective future. Electrical Power Quality and Utilisation (EPQU) (2011)
6. Al-Awami, A.T., El-Sharkawi, M.A.: Coordinated trading of wind and thermal energy. IEEE Transactions on Sustainable Energy 2 (3) (2011)
7. Cena, A.: The impact of wind energy on the electricity price and on the balancing power costs: the Spanish case. In the European Wind Energy Conference (EWEC), Marseille, France, Mar. (2009)
8. El-Fouly, T. H. M., Zeineldin, H. H., El-Saadany, E. F., Salama, M. M. A.: Impact of wind generation control strategies, penetration level and installation location on electricity market prices. IET Renewable Power Generation, 2(3):162–169 (2008)
9. Angarita, J. L., Usaola, J., Martinez-Crespo, J.: Combined hydro wind generation bids in a pool-based electricity market. Energy Policy, 79(7):1038–1046 (2009)
10. Bathurst , G. N., Strbac, G.: Value of combining energy storage and wind in short-term energy and balancing markets. Electric Power Systems Research, 67(1):1–8 (2003)
11. Gonzalez, J. G., Muela, R. M. R., Santos, L. M, Gonzalez, A. M.: Stochastic joint optimization of wind generation and pumped-storage units in an electricity market. IEEE Transactions on Power Systems, 23(2):460–468 (2008)

12. Hedman, K., Sheble, G.: Comparing hedging methods for wind power: using pumped storage hydro units vs options purchasing. In International Conference on Probabilistic Methods Applied to Power Systems PMAPS, pages 61–66, Stockholm, Sweden (2006)
13. Bathurst, G. N., Weatherill, J., Strbac, G.: Trading wind generation in short term energy markets. IEEE Transactions on Power Systems, 17(3):782–789 (2002)
14. Matevosyan, J., Soder, L: Minimization of imbalance cost trading wind power on the short-term power market. IEEE Transactions on Power Systems, 21(3):1396–1404 (2006)
15. Pinson, P., Chevallier, C., Kariniotakis, G. N.: Trading wind generation from short-term probabilistic forecasts of wind power. IEEE transactions on Power Systems, 22(3):1148–1156 (2007)
16. Ruiz, P.A., Philbrick, C.R.,Sauer, P.W.: Wind power day-ahead uncertainty management through stochastic unit commitment policies. Proc. IEEE/PES 2009 Power Syst. Conf. Expo. (PSCE\'09), pp.1 -9 (2009)
17. Fan, S., Liao, J.R., Yokoyama, R, Chen, L. N, Lee,W. J.: Forecasting the wind generation using a two-stage network based on meteorological information. IEEE Trans. Energy Convers., vol. 24, pp. 474–482 (2009)
18. Kusiak, A., Zheng, H. Y., Song, Z.: Wind farm power prediction: A data-mining approach. Wind Energy, vol. 12, pp. 275–293 (2009)
19. Catalão, J. P. S., Pousinho, H. M. I., Mendes, V. M. F.: An artificial neural network approach for short-term wind power forecasting in Portugal. Eng. Int. Syst., vol. 17, pp. 5–11 (2009)
20. Catalão, J. P. S., Mariano, S. J. P. S., H. M. I., Mendes, V. M. F., Ferreira, L. A. F. M.: Short-term electricity prices forecasting in a competitive market: a neural network approach," Electr. Power Syst. Res., vol. 77, pp. 1297–1304 (2007)
21. Coelho, L. D., Santos, A. A. P.; A RBF neural network model with GARCH errors: Application to electricity price forecasting. Electr. Power Syst. Res., vol. 81, pp. 74–83 (2011)
22. Amjady, N., Daraeepour, A.: Mixed price and load forecasting of electricity markets by a new iterative prediction method. Electr. Power Syst. Res., vol. 79, pp. 1329-1336 (2009)
23. Floudas, C.A., Xiaoxia, L.: Mixed integer linear programming in process scheduling: modeling, algorithms, and applications. Annals of Operations Research 139, 131-162 (2005)
24. http://www.esios.ree.es/web-publica/