Renewable Energy 101 (2017) 907–918

Contents lists available at ScienceDirect

Renewable Energy

journal homepage: www.elsevier.com/locate/renene

Wind farms participation in electricity markets considering uncertainties

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A R T I C L E I N F O

Article history:
Received 26 April 2016
Received in revised form
11 August 2016
Accepted 22 September 2016

Keywords:
Wind farm power
Uncertainties
Confidence level
LMP
Social welfare
Electricity market

A B S T R A C T

Rising global temperature and environmental pollution as well as the demand for energy consumption have made finding new and affordable clean energy resources a serious challenge for governments. A possible solution could be renewable resources such as solar, wind or geothermal energies. Restructuring and deregulation have provided a competitive environment which makes analysis of these new energy sources necessary. Wind farms have been receiving more attention from governments because of their noticeable generation capability. The stochastic nature of the wind inflicts uncertainty on the output generation of wind farms which then causes some limitations for the participation of these farms in the electricity market. Thus, in this paper the effects of uncertainty in predicting the wind farm's power on locational marginal price in the market have been studied. According to the advantages and disadvantages of wind farm's power uncertainties, a procedure to maximize the social welfare **is** presented. The studies have been done on an 8-bus network for 24 h in a day-ahead electricity market. To do this, the farm power is predicted using Neural Network and Wavelet Transform and its uncertainties are calculated using the asymmetric Quantile Regression method.

1. Introduction

Environmental pollution, global temperature rise, fossil fuels shortage crisis and technology advancements have forced governments to consider using renewable resources such as solar, wind or geothermal energies. Moreover, restructuring and deregulation have produced a competitive economically opened environment which in turn has naturally increased the system efficiency. Therefore, of great importance is the investigating the economic effects of new equipment installed in the power network in this new environment [1]. Power generation using the wind, free and environment-friendly and having low repair and maintenance costs with quite high generation capability, has been increasing due to the growth in the use of wind farms in power networks. In spite of improvements in the generation and increased penetration in power systems, wind farm participation in the Electricity markets remains a real challenge because of their intermittent nature [2].

Market participants need to predict the power of wind farms for market closure. In doing so, There are several procedures including combining Fuzzy Logic and Neural Network, known as Fuzzy Logic-Neural Network methods [3,4], using Kolmogorov-Zurbenko filters, Markov-Chain model, and Wavelet Transform to eliminate temporal pulsations of the wind or wind farms power [5], combining adaptive wavelet neural network and feed-forward neural network [6], or using wavelet transform and Radial Basis Function network [7]. Moreover, the variation of the output power of wind turbines is a real challenge for the safe and economic performance of power systems; therefore, calculating uncertainty in the output power prediction is now inevitable for beneficiaries to making decisions.

One of the most common methods of uncertainty calculation is the Monte Carlo simulation. Unfortunately, since having a high program running rate and requiring the probabilistic distribution, this method is time consuming. The Point estimation technique is another method, unlike the Monte Carlo simulation, uses multiple points (one or two points), and thus reducing the number of calculations considerably [8,9]. Additional information about different methods of analyzing uncertainty in the predicting wind turbines can be found in Refs. [10–12]. Another important element in the calculation of uncertainty is prediction intervals (PIs) which, providing a lot of information about unknown uncertainties around the predicted points by defining specific Confidence intervals. Several methods have been offered for establishing prediction

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http://dx.doi.org/10.1016/j.renene.2016.09.049
0960-1481/

Nomenclature

Indices

I	Index for buses
J	Index for Generators

Sets (Variables)

P	Amount of active power
I_i	Injected power
P_d	Active power demand.
V_{t+k}	Velocity at time t + k
P_t	Wind farm's power at time t
P_{t+k}	Wind farm's power at time t + k
a,b,c	Cost functions' Coefficients
μ	Coefficient related to spot price.
Y_{ij}	the ith row and jth column of the admittance matrix
Θ_i	the angle of bus i
P_{ij}^{max}	the maximum power flow through the line i-j.

intervals using a Neural Network [13,14], the main drawbacks of these methods are again being highly time consuming, requiring a large amount of calculations and the necessity of specific probabilistic distributions. Attracting a lot of attention in recent years, Quantile Regression (QR) has been proven to be one of the most effective methods [15]. It features fast and easy calculations, having no need for probabilistic distributions, and not using the smart methods like Neural Network. Uncertainty in the power generation, risk of participating in the market and return of fund are other factors which effect the participation of wind farms in the market.

The need of wind farm owners and system operator to develop a strategy covering all above factors has been investigated in several studies. Many wind farm owners in the USA are selling their power through a long-term contract and with a fixed price [2]. In Ref. [16] the impact of different prediction methods on the wholesale price of wind power has been studied. In Ref. [17] reducing unbalanced price in short-term markets is investigated using a probabilistic Markov model. Research done in Ref. [18] used the Quantile Regression probabilistic power prediction method to discuss how wind farm performance can be used to maximize the acquired interest. In Ref. [19] the probabilistic distribution of unbalanced prices has been predicted and an optimized bidding procedure has been offered to participate in the market using the Kernel density estimation (KDE) method and the Conditional value at risk (CVAR) technique considering uncertainty. Wind energy trading in real-time and day-ahead markets have been studied in Ref. [20], and a balance between the risk and the recessive expenses of the wind farm was provided based on locational marginal price (LMP). Having considered the penalty factor and LMP [21], formulizes the wind farm contract optimization.

An important point that should be considered is that due to their rather high rate of generation, wind farms can affect the losses rate and increase congestion of the lines, affecting the generation capability of other units and the prices of the market. Power and uncertainty variations in the prediction complicate these affectations as well as decision making about the market. In the most recent studies in this area [22], an optimal bidding strategy is presented for a multi independent wind farm with the aim of maximizing 24 h social welfare in Oligopolistic Day-Ahead. Optimal bidding and generated scenarios for uncertainties in generated power were modeled by the Stochastic Cournot Model and Auto Regressive Moving Average (ARMA), respectively. This method requires a lot of computation; consequently, decreasing scenario methods are necessary for fewer calculations.

To the best of our knowledge most of the studies on wind power and its uncertainties in the electricity market are based on the point estimation (special value is allocated to the special value of wind) and the scenarios (dependent on many calculations) while the effects of the upper and lower bands and the probabilistic intervals (PI) created between the two bands in the context of the market price, profits and losses of participants and the optimal amount for wind power to maximize the social welfare are rarely considered [23].

Therefore, in this paper the impacts of uncertainty in predicting wind farms power on LMP in the market considering PIs has been studied, and a new method for an optimized amount provided by the wind farm in order to maximize producers and consumers profits (social welfare) has been offered. Optimal wind power tries to achieve the maximum possible profit for winners in every hour and the least amount of loss for the losers. In this study, the network was analyzed using DC optimal power flow (DCOPF) without considering the losses of the lines, and the wind farm modeled as a negative load without assuming a specific price for its power generation. To analyze LMP, the market has been run hourly and the electricity market is considered as a day-ahead market. As opposed to many references neglect the effect of network topology (such as congestion) on the issue, network topology has been considered in this paper since it has an effect on the process of the issue as well as the reality. The rest of the paper is organized as follows: in Section 3 wind farm power prediction methods are introduced and uncertainty in predicting the power of wind farms is studied. In Section 4 impacts of wind power and its uncertainties on LMPs are presented. In Section 5 the issue is formulized and a new strategy is provided so as to improve LMP and optimize social welfare. Finally, the conclusion is provided in the last section.

2. Wind farm power predicting and uncertainty analysis

2.1. Prediction

In this paper, the wavelet transform and radial basis function Neural network method has been used to predict wind speed [7]. The data set having been used for teaching purposes and testing the Neural Network includes speed, direction, humidity, and temperature. Considering contiguity of the turbines, locational characteristics, and the effects of the turbines site, in Ref. [24], the non-polynomial equations method is offered to calculate the output power of the turbines of Tetrapolis Kefalonia wind farm located in Greece with maximum capacity of 32.2 MW [24,25]. Using this method, the power of the turbines was calculated using Equation (1).

$$P_{t+k} = 403.51 \tanh\left(\frac{v_{t+k} - 9.1}{2.864}\right) + 0.025P_t + 407.6 \tag{1}$$

Due to Tetrapolis wind farm's high generation capacity and more useful formula for calculating the power, this wind farm has been studied in this research. The wind speed is predicted by means of Wavelet- Neural Network method. Therefore, the power of the wind farm is calculated for a day using Equation (1) (11 May 2014). Power of wind farm based on the predicted speed is shown in Fig. 1.

2.2. Calculating uncertainty in predicting the power of wind farms using the Quantile Regression method

One of the most efficient methods for uncertainty calculations is the Quantile Regression method. It does not use a specific

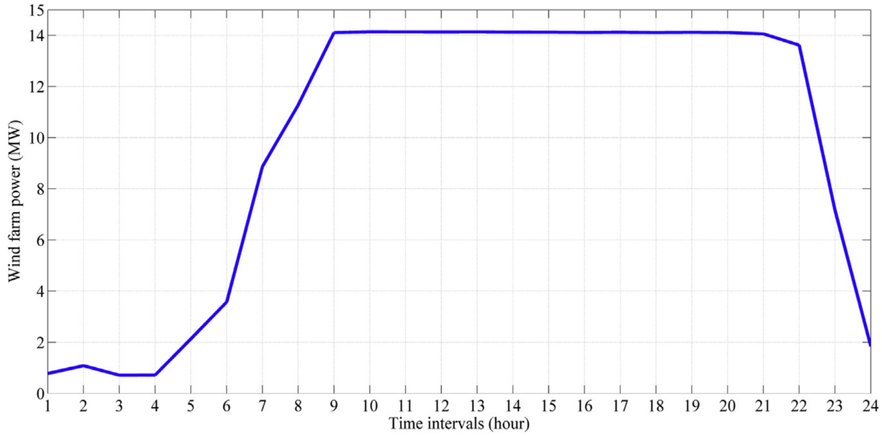

Fig. 1. Predicted wind farm power.

distribution to calculate uncertainty in prediction and provides a more exact rate of prediction error. Other advantages include its low amount of calculations in action and establishing prediction intervals without using methods like Neural Network; therefore, the Quantile Regression method has been used in this study to calculate uncertainty [15].

The power and its related uncertainty for a 95% confidence level are depicted in hourly average in Fig. 2.

3. Impact of wind power and uncertainties on LMPs

3.1. LMP formulation

Social welfare is the difference between the costs of the generated C(P) energy and the consumers benefits B(P):

$$\text{Social Welfare} = \sum \mathrm{B(P)} - \mathrm{C(P)} \tag{2}$$

The clearing price is determined by optimizing this function with the Independent System Operator (ISO) considering the constraints of the system. In most cases there is either no specific formula for B(P) or it is very complex. As a consequence, B(P) is neglected and the following function is minimized (according to the negative sign) [26]:

$$\min\left(\sum_{i=1}^{n} \mathrm{C_i(P)}\right) \tag{3}$$

where $C_i(P)$ is the cost function of every generator and is usually explained with $C_i = aP^2 + bP + c$, in which n is the number of generators and P is the generated power. Equation (3) can be solved based on DCOPF [27]. In this situation the Lagrange function of optimization problem is derived as follows:

$$l = \sum_{i=1}^{n} C(I_i) + \sum_{i=1}^{n} \pi_i \left[I_i - \sum_{j=1}^{n} Y_{ij}(\theta_i - \theta_j) \right] + \sum_{i=1}^{n}\sum_{j=1}^{n} \mu_{ij}\left[P_{ij}^{\max} - Y_{ij}(\theta_i - \theta_j) \right] \tag{4}$$

In (8) π_i is the LMP for the bus i.

It should be noted that according to DC load flow, cost of power loss have been neglected and the calculated price included prices of slack bus and congestion of the lines. Since losses price has a negligible effect on LMP in comparison with slack bus price and transmission line congestion, it has been neglected and DCOPF has been used [28–32].

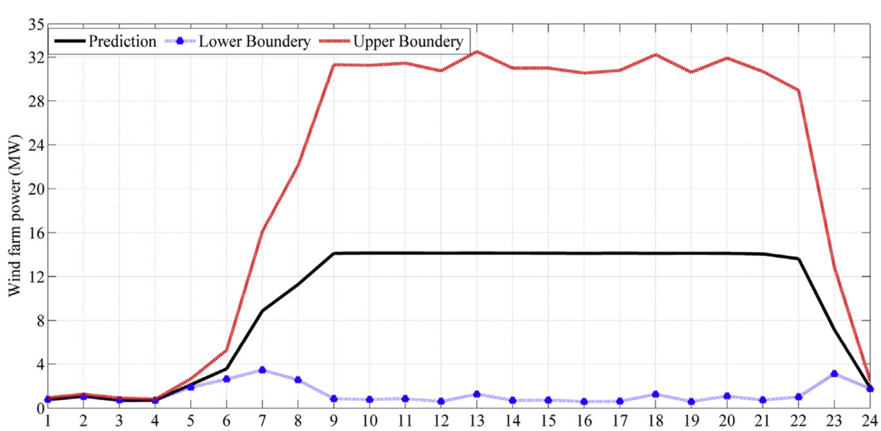

Fig. 2. Uncertainty in predicted power with 95% confidence level.

3.2. Network configuration

The studied network is an 8-bus transmission system which is depicted in Fig. 3 [33]. Cost of power generated by wind farm has been neglected and the wind farm is like a load with negative value injecting power into the network. The results of power prediction and uncertainties in the previous sections have been used for the simulation.

3.3. Bringing wind energy in electricity market

The day-ahead market has been run hourly using the results of the predicted uncertain power and the scale factor of the loads curve of the day (shown in Fig. 4.). Through optimization method (DCOPF), could calculate the amount of power plants' generation, LMPs and Lagrange factors relating to the stipulated sum of the power of the nodes. In Fig. 5. LMPs are shown within 24 h and in different situations of uncertainties.

According to Fig. 5a., the most expensive and the cheapest buses are buses 2 and 1, respectively. The price of the cheap buses did not change with the use of a wind farm with the predicted power. On the other hand, the price of the expensive buses is reduced to the least amount of LMP within 24 h and remained stable (Fig. 5b.). In other words, applying a cheap energy generation source made no change in the cheap buses, but lowered the price of expensive buses as much as possible. As it does not hold a noticeable amount of energy, the lower band of the power of the wind farm did not affect the LMPs much; it only lowered the LMPs slightly as seen in (Fig. 5c). According to Fig. 5d., applying the upper band of the predicted power had no effect on the price of buses 1, 5 and 6 similar to the previous cases, but it did fix the price of buses 3, 4, 7 and 8 on the least possible value; and it has decreased the price of the bus connected with the wind farm to a negative value in an interval with noticeable power. In consumer's point of view, bus 2 has ideal price, but not for the farm owner.

The amount of money paid by consumers to consume energy can be calculated by using Equation (5), and the cost of energy generation for power plants as well as the earned revenues can be calculated by using Equation (6).

$$Cost\ Demand_i = \pi_i \times Pd_i \tag{5}$$

$$\mathrm{Revenue}_{G_j} = \pi_i \times P_j - \mathrm{Cost}_{G_j} \quad i = 1, \ldots.., 8 \quad j = 1, \ldots.., 6 \quad Cost_{G_j} = aP_j^2 + bP_j + c \tag{6}$$

Figs. 6 and 7 show the amount of the power plants' revenue and consumers' payments, respectively.

As shown in Figs. 5b and 6b., when the amount of wind farm power is equal of predicted power, the LMP in all buses decreased while revenues increased to the maximum possible value among all the plants. Also, G2 and G6 similar to other generators, not only did

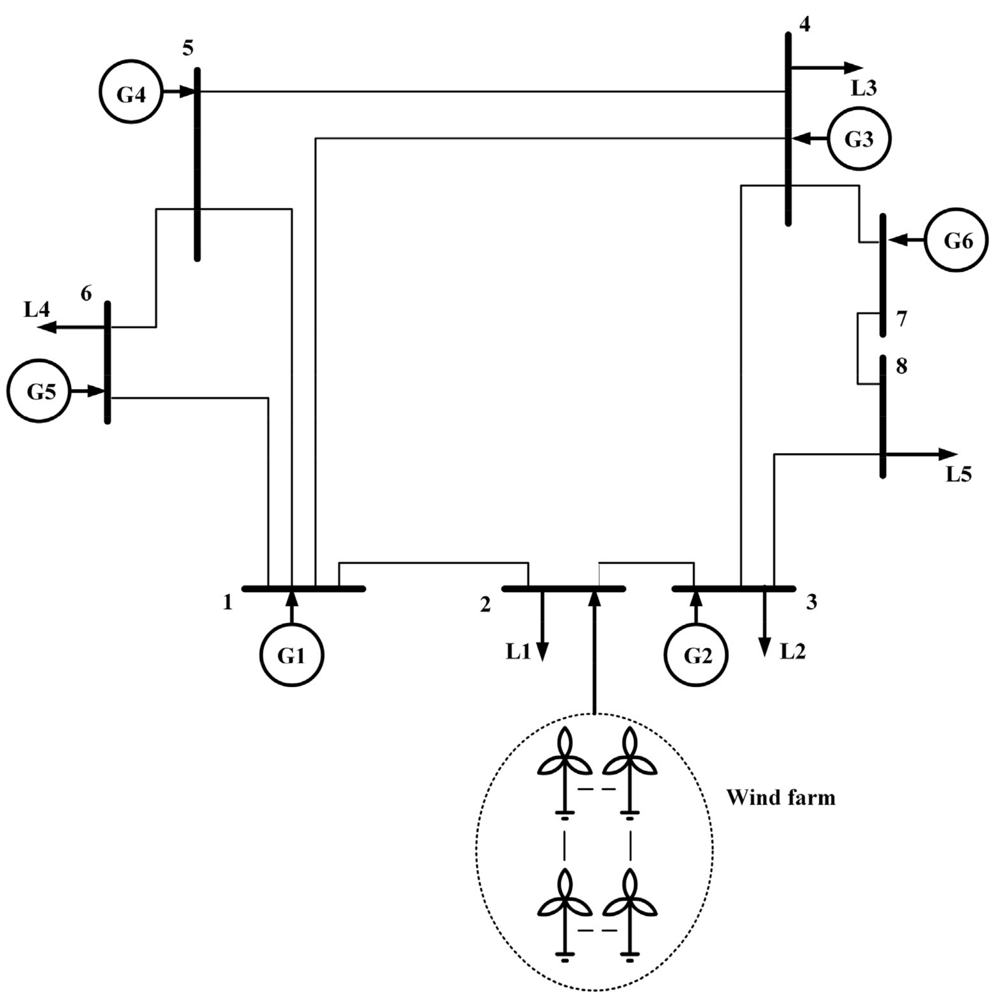

Fig. 3. Single line diagram of 8-bus test system.

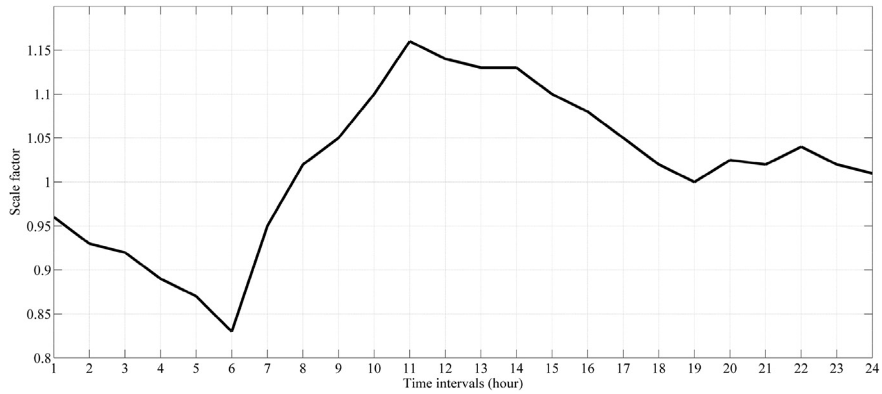

Fig. 4. Load scale factor.

not receive any benefits but also had negative profits most of the time, and as this is not favorable for them, they did not contribute to the market during these periods. In other words, this amount of wind power cannot proper for the social welfare. From the consumers' point of view (Fig. 7 b.) there was a reduction in energy payments, so this offer is more acceptable to them. The reduction in LMPs were not equal in every bus and the reduction was considerably more in some buses than others.

If the lower bound of wind farm power injected to the power (Fig. 6 c.), according to the least amount of the power, the plants' profit was not considerably affected in comparison to the absence of wind power. It is noteworthy that even though the least amount of wind power has been offered, the wind farm still made its profit due to the high price of the bus 2.

Upper bound of the predicted power not only caused negative profits for G2 and G6 but also the wind farm experienced a financial loss during most periods of the day despites having considerable produced power. The wind farm's loss was considerably more than the other plants. This situation is not acceptable to the wind farm owner and the other ones. However, from D2, D3, D4 and D5's point of view the payments reached the minimum possible value, similar to the situation in Fig. 7 b. D1 in bus 2 -where the wind farm is connected-obtained the maximum profit in most periods of the time due to negative LMP.

In order to clarify the impact of wind farm on the market, the total 24 h profits and payments have been considered from other viewpoint. As it can be seen from Fig. 6 a–d and the amount of power produced by power plants G1 to G6 which is resulted from DCOPF, G2 and G6 produced the majority of required market's power and made profits in all four scenario a-d and other power plants made loss most times. Based on the mentioned reasons two power plants G2 and G6 with wind farm have been examined from producers' profit point of view. For this purpose, their 24-h profit in the day ahead market are calculated according to Fig. 6 a–d and shown in Table 1. The consumers' payment in 24 h are shown in Table 2.

According to Table 1 the amount of total profit of power plants is maximized in the applied predicted wind power scenario, and the wind farm received the maximum profit among all scenarios. On the other hand, this led to negative profit for other two plants and this is not good for the owner of these two power plants, so applying the predicted power does not seem appropriate from their viewpoint. By applying the predicted upper band, all the producers made loss and could not be regarded as a desired case for them. In two scenarios, without wind farm and applying the lower band of wind power, the values were relatively close together; whereas the wind farm gained relatively high profit along with other producers and profit of other two power plants reduced in the lower band power scenario. However, the profit increased 526.7$ compared to the without wind farm scenario. From analysis it is concluded that the applying the lower band of wind farm would be the most desirable mode for producers and wind farm.

Regarding Table 2 and from the consumers' viewpoint, applying the upper band of predicted power would provide the condition so appropriate that the amount of their payment has decreased 23633$ in comparison to without wind farm scenario. It can be seen that applying a specific range of wind power is suitable from point of view of producers or consumers. In order to achieve a better analysis of the results an index is defined as follows (payment and revenue difference index):

$$PRDI = \sum_{h=1}^{24}\left(\sum_{j=1}^{5} Payment_{Dj,h}\right) - \sum_{h=1}^{24}\left(\sum_{j=2,6} \mathrm{Re}venue_{Gj,h} + \mathrm{Re}venue_{WF,h}\right) \tag{7}$$

From (7) it can be concluded that the more 24 h revenue or the less total 24 h payment is achieved, the less the PRDI would be. As this index reduces, the condition would be desirable for market participants respectively. Therefore, the ideal situation would be realized when the first term is minimized and the second term is maximized. The index would not be defined in the scenarios, such as applying the lower band or anticipated power, in which the profit is negative and improper. Otherwise a negative penalty factor should be multiplied in the second term to define this index. The amount of PRDI for two acceptable forms of wind power (without wind farm and lower band of predicted wind power) are calculated as 58055($), 54087.3($), respectively. With regard to resulted values, applying the lower band is better for both producers and consumers.

According to Fig. 5 a–d, the injected amount for the wind farms power in the market affects the LMPs. As can be easily seen in Figs. 6 and 7, Tables 1 and 2, if the wind farm injected high power the consumers will make the most profit in the market. In the case of lower band of power both the wind farm and the consumers will make profit. The rest of the power plants, however, will have a loss. In fact, a wind farm has the power to affect the market and competitions (social welfare). Moreover, since a wind farm is considered as a negative load and the network consumes all it generates, in the market it needs to behave in a way that keeps both producers and consumers satisfied and help to maximize the social welfare. Also, the wind farm owner has an interval of power values with

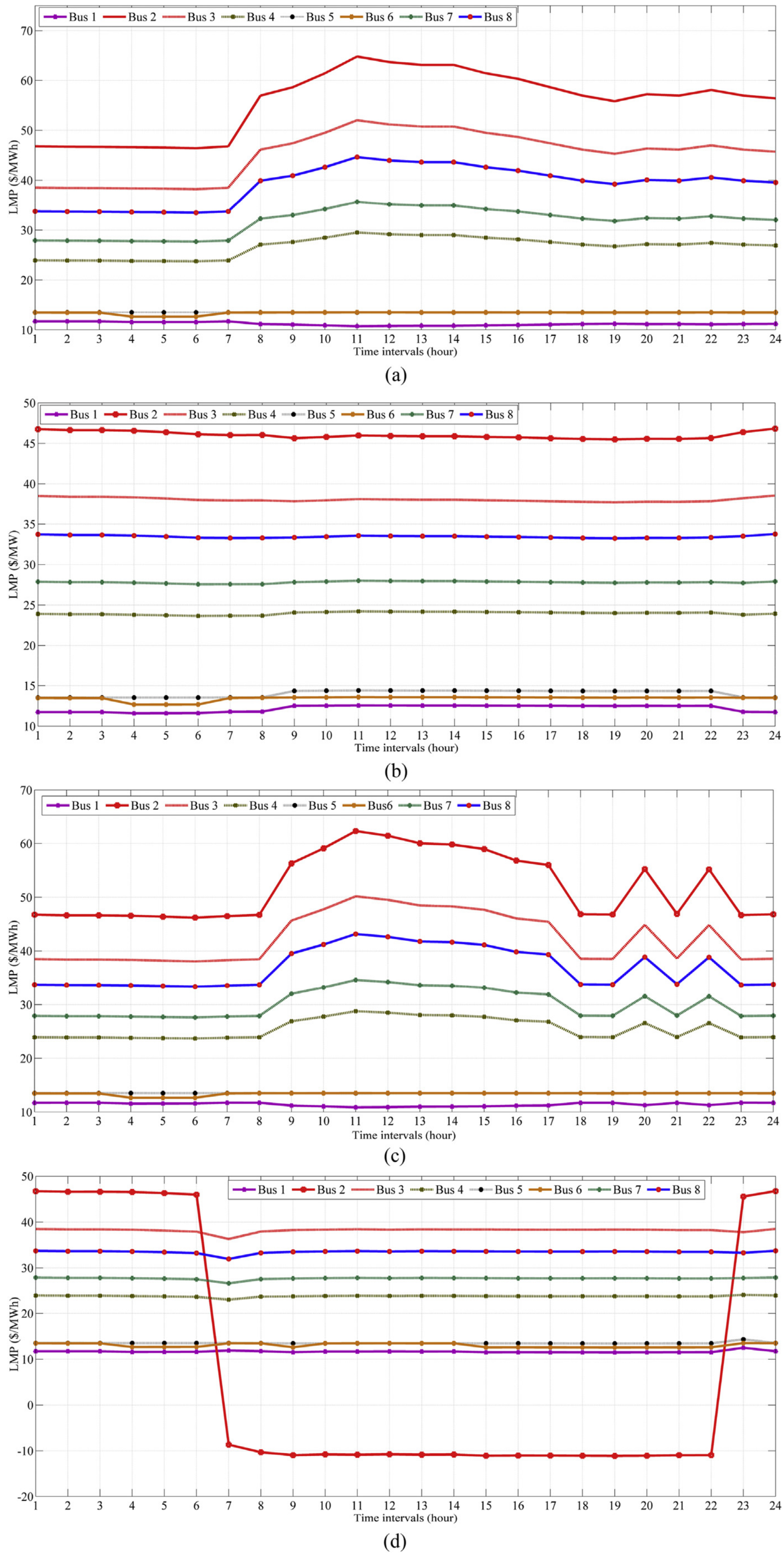

Fig. 5. LMP in different condition. a. without wind power, b. with predicted power, c. with lower band of wind power, d. with upper band of wind power.

high confidence level (95%) for an hour instead of a single value and each of these values will be possible for that hour. Therefore, a method has to be offered that enables an independent system operator (ISO) to decide for the participants. In other words, the system operator has to decide for the electricity market using an interval of the generated power from the wind farm owner and calculate the optimized LMPs to reach the maximum social welfare. In other words, there is a unique probability for the likelihood of each value occurring between the upper and lower bound (PI); hence, the scheduling of the each selected PI value causes some to make more profits and some to lose more. Optimal decision of the predicted wind power must be done in such a way that selection among the PI (in each hour) maximizes the social welfare and satisfies these conditions:

1 All the winner participants who made their maximum profit in accordance with the special selected value of PI must obtain the same profit.
2 All the losers who made their minimum loss in accordance with the special selected value of PI must obtain the same loss.

4. Social welfare maximizing strategy considering uncertainty

All points between the upper and the lower bands of the wind farm attained in a particular hour produce LMP and several LMPs may be assumed for every bus, each of which has a specific probability. Among these many points one optimized point has to be chosen that favors both producers and consumers. To do this, a new objective function was suggested to maximize the social welfare. The amount of power a wind farm can produce is probabilistic, and if it is not able to generate the scheduled power at the appointed time it will have to pay a penalty. To make a model of the error rate in the amount of power a wind farm produces the probability of each possible point has to be determined. Due to the high level of confidence considered in uncertainty calculation, power probability is very high in the upper and the lower bands (95%) and very low elsewhere. Thus, forbearing outside this interval, the method below was suggested to attribute a probability to each point. The spacing between the upper and the lower bands in every hour is divided into N equal parts.

1) The point relating to the predicted power was used as the reference point of the calculations. The highest amount of probability, 95%, was attributed to this point. The reason for doing this is that this point was attained through advanced and accurate methods of prediction, so its probability has to be more than that of the other points.
2) Starting from the reference point and going up, the size of one of the N equal parts is added to the value of the reference point in each step. But in turn, it loses 5% of its probability.
3) The same as step 2 but going down this time. The size of one of the N equal parts as well as 5% of probability is taken from the reference point.
4) Steps 2 and 3 are repeated until reaching the upper and lower bands boundaries to assign the spacing between bands and the intervals of probability.

The diagram of the suggested method is shown in Fig. 8. In the previous section, it was found that wind farms produced clean and low cost energy and reduced the LMPs. Due to these advantages and making the assumption that wind farms behave like a load, all the wind power injected to the network in every hour, which would be determined by the operator's decision must be used by the consumers. If an error occurs in the presentation of the scheduled power, the wind farm must be punished with a penalty factor. Indeed, (1-Probability) shows the maximum failure to reach the offered power. This lack of power must be taken over in the spot market. In order to supply energy with a spot market, its price could follow Equation (8) in every hour.

$$\text{Spot price}(t) = \mu \times \text{Max}\ (\text{LMP}(t)i) \quad i = 1, 2, \ldots, 8 \tag{8}$$

LMP $(t)_i$ is the LMP at hour t in bus i.

The money required to provide for the lack of the energy from the spot market must be taken from all the participants. Accordingly, the objective function below was suggested to calculate the optimized power of a wind farm.

$$\begin{aligned}\text{Min}\Bigg[&\sum_{i=1}^{8} C_i(P(t)) + \text{ Penalty factor}(t)\\ &\times \text{ Windfarm power}(t) \times (1 - \text{Probability}(t))\\ &+ \text{ Windfarm power}(t) \times (1 - \text{Probability}(t))\\ &\times \text{ Spot price}(t)\Bigg]\end{aligned} \tag{9}$$

Having resolved the optimization problem, the amount of wind farm power needed to keep both consumers and power plant and wind farm owners satisfied (maximize the social welfare) in every hour and to ensure network security was calculated. Supposing the penalty factor to be 5($/MWh), the μ factor to be 1.1 for every hour and N = 20, and minimizing Equation (9), the amount of optimized wind farm power, optimized LMP, and the generation of other power plants have been calculated.

Fig. 9 a. represents the amount of the wind farm power appointed by the system operator for every hour. The amount of the LMP of different buses is shown in Fig. 9 b. Applying the suggested optimized amounts led to minimizing the bus prices, as applying the upper band of the farm power does, but the price of bus 2 was no longer negative for any extended amount of time. In some intervals, however, the price was inevitably negative, but these intervals are very short compared to intervals that did not so. This means that hours of making profit for the farm have increased.

The amount of power plant revenue is shown in Fig. 9 c. As can be seen, power plants G2 and G6 have the same behavior (Fig. 6 a.) after applying the suggested optimized amounts. Nevertheless, the wind farm have made a noticeable profit except in special intervals. The intervals in which the farm makes profit will significantly increase, and vice versa.

WF-max in Fig. 9 c shows the wind farm's profit when the calculated wind power with the special probability occurred. WF-min shows the wind farm's profit when there was an error set to (1-probabilty) and the penalty factor was imposed on the wind farm's profit. The amount of money paid by the customers is shown in Fig. 9 d. In consumers' view (D2 to D5) their payments reached the lowest amount among the explained situations (similar to the state of selecting the predicted power) and they made a profit. Considering the optimized value, in bus 2's view negative intervals have decreased which is good for the wind farm, but there are still negative intervals in which D1 makes profit. In other words, the ISO has considered the profits of both sides and maximized the social welfare. Also, in positive intervals D1's payments have decreased comparing to the discussed situations which is again in D1's favor.

For comparison with analysis of previous section and investigating the effectiveness of proposed method, total 24 h profit, total consumers' payment, and PRDI index in this mode are given in Table 3.

According to Table 3 total consumers' payment are dropped

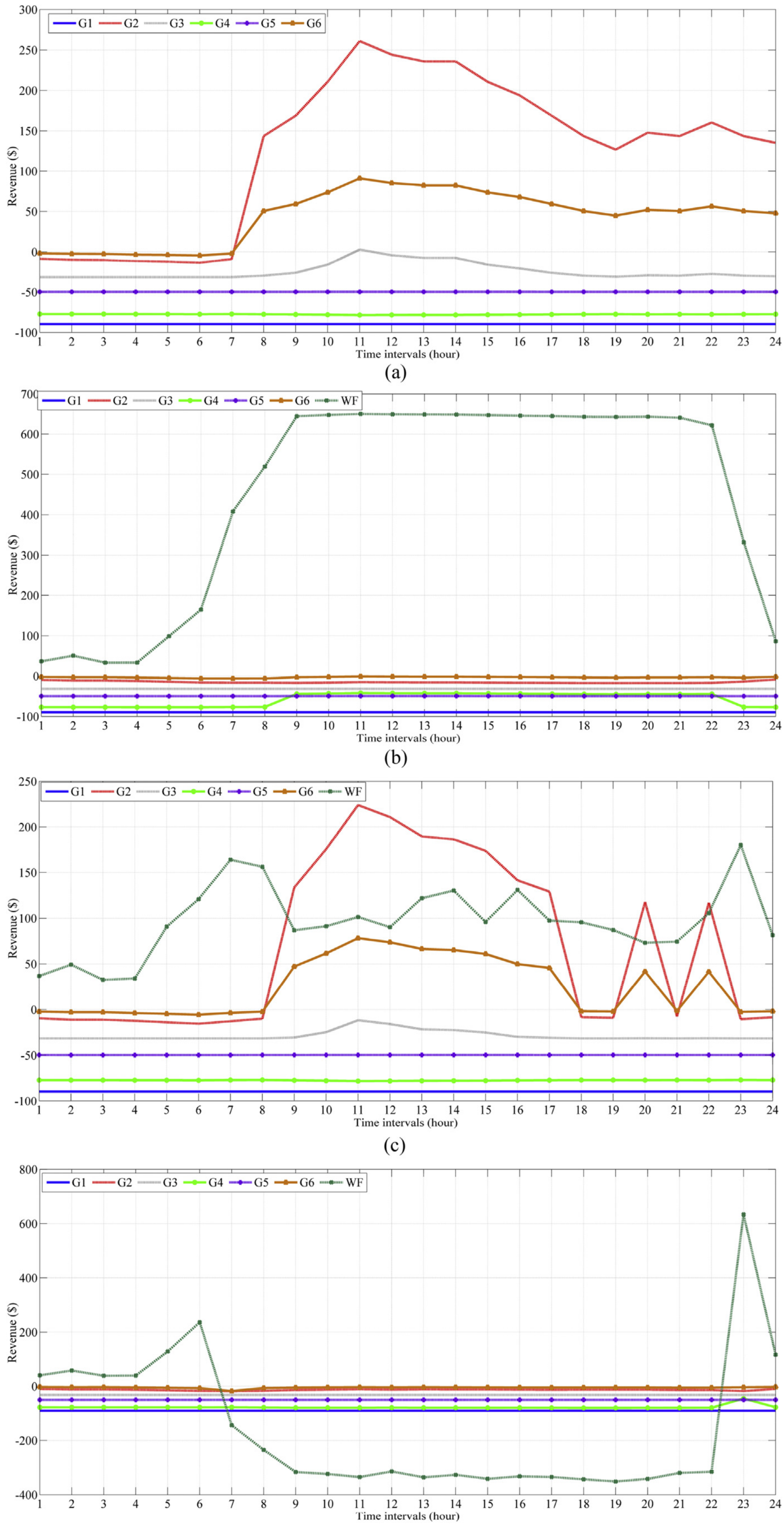

Fig. 6. Power plants' revenue in different condition. a. without wind power, b. with predicted power, c. with lower band of wind power, d. with upper band of wind power.

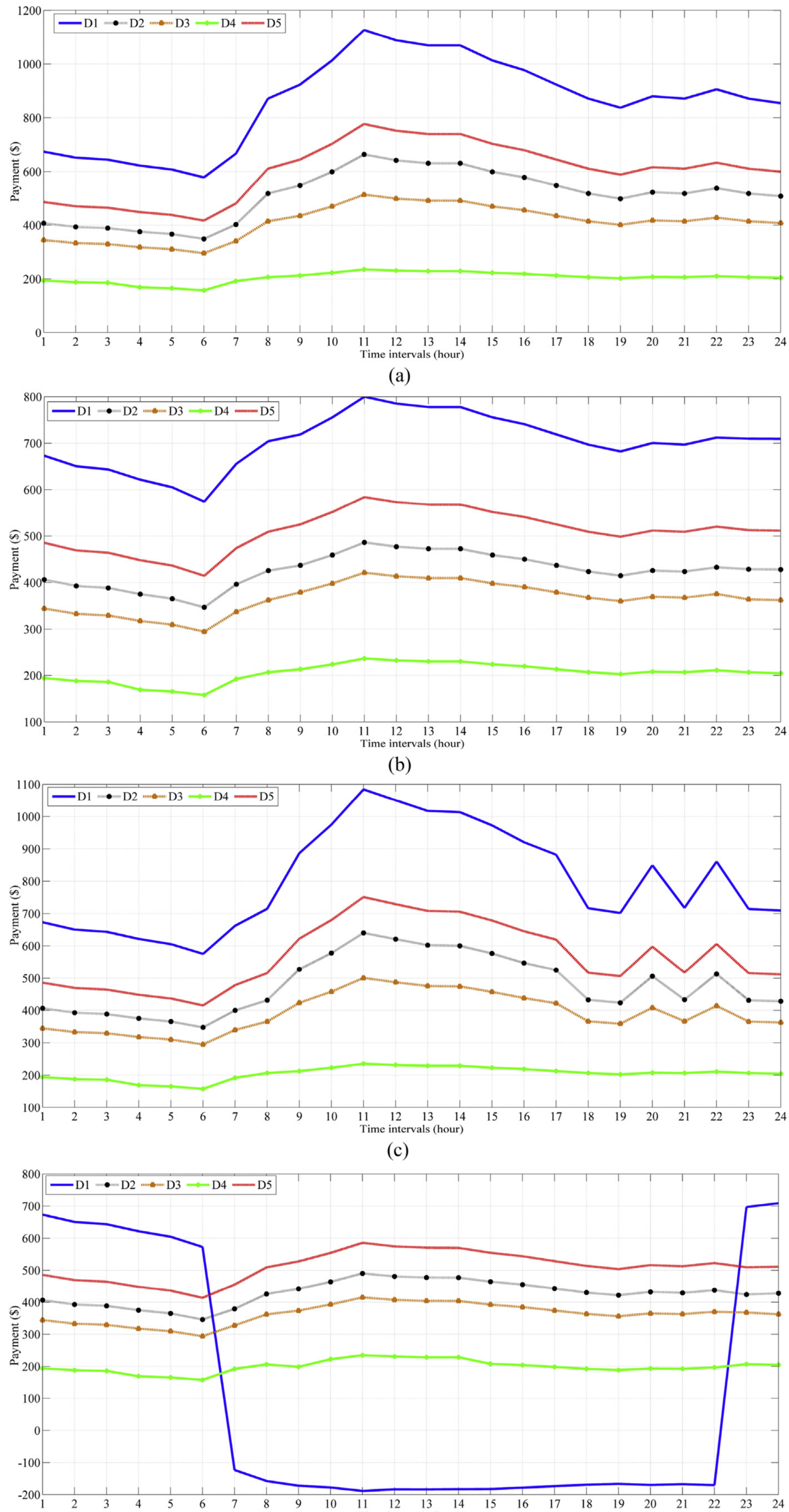

Fig. 7. Consumers' payment in different condition. a. without wind power, b. with predicted power, c. with lower band of wind power, d. with upper band of wind power.

Table 1
Total revenue of power plants in 24 h for different wind farm power.

Scenarios	Total revenue of power plants ($)			
	G2	G6	WF	Total
Without wind power	2997.8	1056.2	0	4054
Predicted power	−361.91	−75.1	10776	10339
Lower band of wind power	1658.3	593.8	2328.6	4580.7
Upper band of wind power	−307.96	−109	−3718.05	−4135.01

Table 2
Total consumers' payment in 24 h for different wind farm power.

Scenarios	Without wind power	Predicted power	Lower band of wind power	Upper band of wind power
Total Payment ($)	62109	53082	58668	38476

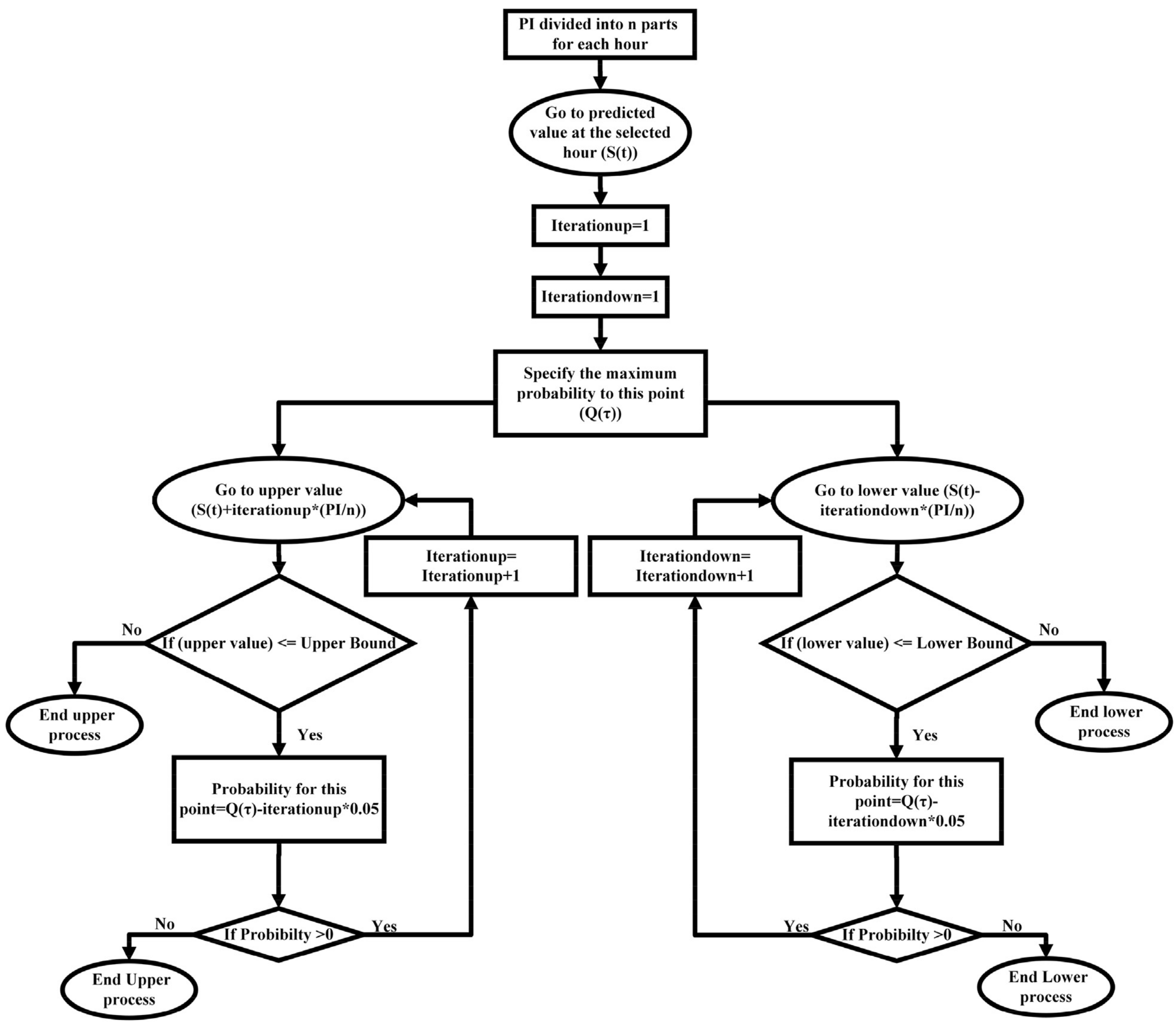

Fig. 8. Flowchart of wind power probability appropriation in PI intervals at each hour.

considerably and has come closer to the upper band of wind power. The wind farm received considerable profit in the both case of with and without occurrence of errors, and total received profits of other plants were acceptable and they are in the range of applied predicted power mode which is favorable for all producers. PRDI values are shown in Fig. 10. PRDI values of both optimized cases (WF-min, WF-max) have been significantly reduced in comparison with non-optimized scenarios. Therefore, this reduction indicates the effectiveness of the proposed method in participants' satisfaction and decreasing the index.

5. Conclusion

In this paper, the impact of uncertainty in predicting the power of wind farms on LMP in the electricity market was studied, and an optimal strategy for maximizing the social welfare under uncertainties was proposed. The effects of uncertainty in the predicted power of wind farms on LMP based on prediction intervals

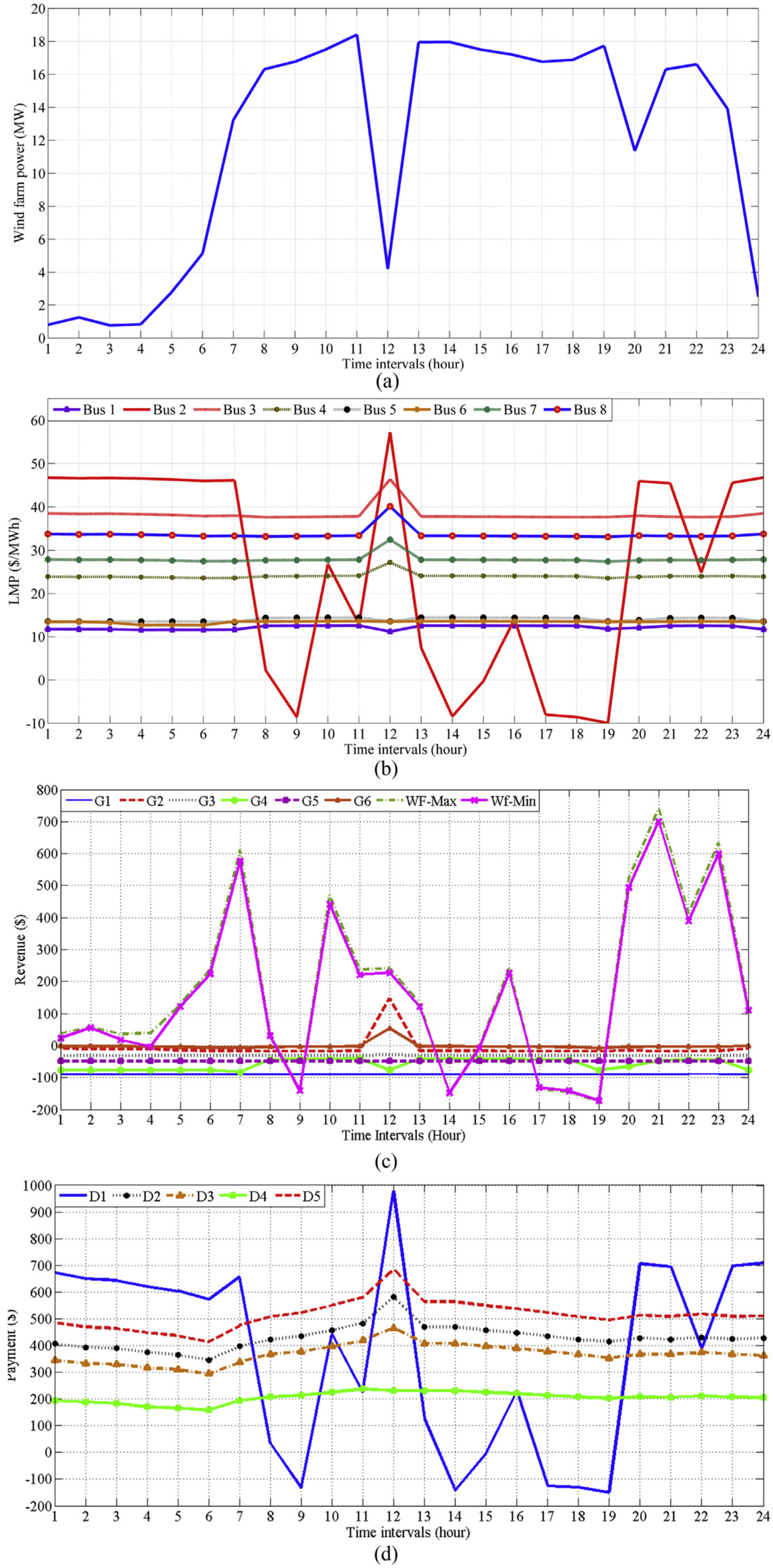

Fig. 9. a. Optimum amount of wind power, b. LMP in optimum value of wind power, c. Profit of power plants achieved in the optimum value of wind power, d. Money paid by the costumers in optimum value of wind power.

Table 3
Total 24 h revenue and payment for Optimum amount of wind power.

Wind farm's total revenue($)		Total revenue of power plants ($)		PRDI ($)		Total payment ($)
WF-max	WF-min	WF-max	WF-min	WF-max	WF-min	
4178.4	3830.4	4434.67	4086.67	41275.33	40927.33	45362

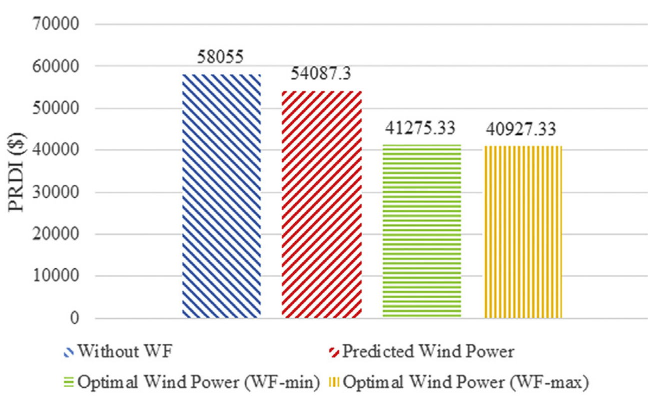

Fig. 10. PRDI in different conditions.

and Quantile Regression were first studied. As it is seen, applying points between the upper and the lower bands of the prediction interval cause profit for some participants and loss for others. A new objective function was then provided for optimizing the value of the wind farm's power so as to maximize social welfare (to increase profit and decrease loss). Using this objective function, tried to maintain the advantages of the points between the upper and the lower bands and lessen their disadvantages as much as possible. The results of the simulations confirmed the effectiveness of the suggested method.

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