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Enhancing Day-Ahead Electricity Market Planning with a Novel Probabilistic Strategy for Wind Power and Uncertain Customers

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Abstract: Nowadays, the participation of wind power plants in electricity markets has become a severe challenge due to their intermittent nature for decision makers of market. In the presence of uncertainties, some sellers and buyers experience a reduction in their satisfaction. This paper presents a new method for the participation of wind power plants and uncertain customers in a day-ahead electricity market based on the local marginal pricing mechanism to maximize the total profits of sellers and buyers considering their importance level through a two-level optimization problem. For this purpose, using the empirical cumulative distribution function and the Monte Carlo method, the uncertainties are modeled. Then, by defining some economic indices to evaluate participants' satisfaction and using the analytic hierarchy process, a new objective function is proposed to optimize the mentioned indices. Simulations are implemented on a realistic 8-bus sample system, and the results confirm the efficiency of the proposed method in significantly reducing the costs of producers and customers, and consequently their total profits. Based on the results obtained from the presented method, the expected ranges for total cost fall between 1,270.91$ and 1,719.50$, while the expected ranges for total payment range from 2,151.41$ to 2,192.58$.

Keywords: *Wind power plant; Uncertainty; Locational marginal pricing; Analytic hierarchy process; Monte Carlo; Radial basis function neural network clustering*

1. Introduction

Recently, with the advancement of technology, the amount of power produced through renewable energy resources has increased significantly which leads to the widespread use of these resources in power systems and electricity markets.

Studies show that in the presence of renewable resources, clearing prices of electricity markets will be reduced [1-3]. These papers focus on optimizing wind power participation in day-ahead electricity markets to minimize costs using a probabilistic approach and meta-heuristic optimization algorithms. Results demonstrate the effectiveness of the proposed method in reducing total expected costs by up to 20 percent. However, due to the inherent fluctuations associated with them, their collaboration in electricity markets presents a considerable problem for all the stakeholders [4, 5]. These studies address the obstacles of incorporating fluctuating renewable energy sources such as wind and solar into electricity markets, highlighting how existing market structures are not well-suited to their unique attributes. They stress the importance of developing new market frameworks that accurately value renewable generation, promote consumer engagement, and stimulate investments in the renewable energy industry. Furthermore, the inherent variability of these sources poses a significant challenge for all parties involved in electricity markets. Tan et al. offer a comprehensive examination of the advancements in locational marginal price (LMP) theory within power systems [6]. They investigate the complexities of pricing in scenarios involving non-convexity, multiple intervals, uncertainty, and distribution systems. They also address the hurdles and advancements in integrating energy storage and renewable generation into LMP frameworks, emphasizing the necessity for innovative pricing strategies and additional research on market structure design and reflecting investment costs. Many investigations have been done on how renewable resources, particularly wind and solar power, should participate in electricity markets. These studies fall into two main categories: The first group evaluates renewable energy resources' participation in the electrical market without considering uncertainties [7-11]. The second, currently attracting significant attention, focuses on renewable energy's market participation while taking uncertainties into account. It should be noted that these uncertainties have two origins: uncertainties due to inherent fluctuating nature of renewable resources and ones due to the inconsistent power consumption of customers such as distribution systems customers. Since the primary focus of this study lies in the incorporation of wind power into an electricity market in the presence of uncertainties, the subsequent section will delve into the review of the second group of related studies.

A wind power plant (WPP) can be used as part of a multi-resource power generation system, including other WPPs, energy storage systems (ESSs), solar power plants, hydroelectric power plants, and thermal units, to help reduce the uncertainties associated with using wind energy. As a consequence, this will lead to an increase in profits for wind power producers and contribute positively to the balance of the power system [12-14]. However, this advantage is achievable for a market participant who holds both wind power assets and another power generation or storage unit. Also, customers' uncertainties are neglected in this case. Demand response programs can also reduce the additional costs imposed by the uncertainty of the power of these resources by 75 percent in the absence of customers' uncertainty [15, 16]. In [17], a demand response model that considers locational marginal electricity-carbon price, wind power uncertainty, and energy storage systems have been proposed to reduce carbon emissions in the power system while maintaining economic operation. Simulation results demonstrate the model's effectiveness in reducing carbon emissions and guiding load consumption from both electricity and carbon perspectives. Additionally, the paper identifies the optimal location for installing energy storage systems.

In [18], Markov probabilities are used to optimize contract energy sales for wind farms in short-term energy markets, aiming to reduce imbalance costs. It highlights the importance of managing commercial risk and considers the impact of market closure delays and forecasting window lengths on the optimal contract level. In [19], the use of probabilistic wind power forecasts through local quantile regression, offering insights into uncertainty in wind power production without distributional assumptions is discussed. It emphasizes the benefits of probabilistic forecasts over deterministic ones and their potential for guiding optimal economic decisions based on quantile forecasts. In [20], a method using Copula functions and MCMC is introduced for forecasting LMP in electricity markets considering wind power output correlation and transmission loss. It demonstrates improved sampling efficiency and more accurate LMP estimation in large-scale systems with multiple wind power sources. The study highlights that integrating stochastic wind power can lead to an increase in LMP on the reference bus while decreasing or even zeroing LMP on other buses, impacting electricity market prices. [21] presents a novel hybrid approach using artificial intelligence and global sensitivity analysis to forecast locational marginal price components in the Mexican Southeast electricity market. It shows the high forecast accuracy achieved by the multi-output model based on artificial neural networks and emphasizes the impact of external factors on electricity prices in the region. In [22], a risk-based decision approach for energy producers trading wind power in short-term electricity markets is introduced. It utilizes wind power probabilistic forecasts to handle uncertainties and reduce penalties for imbalances. The approach aims to enhance revenue by mitigating economic risks linked to wind power forecast uncertainty, highlighting the need for better regulation price forecasting models for further enhancements. In [23], a model and a practical approach for optimizing solar PV power generation in a day-ahead electricity market are presented. Both approaches consider uncertainty levels in power generation, incorporate energy storage systems, and aim to improve efficiency, economy, and reliability in day-ahead electricity markets. The attention should be drawn to the fact that, all the prior studies do not take into account uncertainties among customers or their involvement in ancillary markets. Furthermore, there is no reference to the implementation of incentives or penalties for participants deviating from their predetermined quantities in these studies.

In [24], a model that utilizes stochastic programming and game theory is developed to optimize bidding strategies for wind and conventional power producers in an electricity market. The model includes a bilateral reserve market allowing wind producers to purchase cheaper reserve power to cut costs and increase profits. Case studies demonstrate the model's effectiveness in maximizing profits for wind producers in a competitive electricity market. This study analyzes power plants, including wind farms, under the presumption that they cannot affect the market prices. However, each of them actually possesses some level of market power, which should be taken into account when determining the clearing price. In [25], Dai et al. have proposed models for wind power producers to optimize their bidding strategies in pool-based electricity markets. The models consider uncertainties in system load, wind power production, and bidding strategies of other power producers, emphasizing the importance of risk management. The effectiveness of the models is demonstrated through case studies, showing the impact of wind power penetration on LMPs and the potential for use in larger systems. The trading of wind energy in the real-time and day-ahead markets is examined in [26]. A model for optimal trading of wind power in day-ahead electricity markets under uncertainty, considering settlement mechanisms with locational marginal prices is presented. The model uses kernel density estimation for wind power forecasts, showing the trade-off between risk and return for wind power producers in electricity markets. In [5], the impacts of wind power uncertainty on the LMP in the day-ahead market are examined, and a new strategy for optimal wind farm bidding is presented to maximize social welfare. Additionally, the involvement in the spot market has been taken into account to address the generation gaps resulting from the uncertainty associated with wind power. In this study, similar to [24-26], the effect of customer uncertainty on prices, customer participation in ancillary markets, and consequently the increase of all participants' satisfaction are not considered.

In [27], a robust optimal load flow technique is employed to determine the uncertain components of the locational marginal price, considering the presence of wind resources and uncertain customers. Subsequently, the uncertain locational marginal prices are derived. In this study, customer satisfaction and the impact of parallel markets have not been considered. Also, the impact of each of the uncertainties on producers and customers is considered separately. The allocation of costs due to uncertainties for each participant is examined in [28-30]. In [29], to solve the problem of time-consuming methods based on probabilistic scenarios, the distributional-robust chance constraints method has been used to model the uncertainty. These studies have not taken into account the effects of uncertain producers and customers in ancillary markets. Additionally, these research did not evaluate the satisfaction of all market participants.

According to this literature review and to the best of authors' knowledge, the simultaneous consideration of the uncertainties of renewable resources and customers along with their participation in ancillary markets have not been investigated in previous researches. This paper will therefore explore the involvement of uncertain WPP and customer along with traditional power plants in a day-ahead market with a LMP mechanism considering the spot market. Finally, by planning these participants, an optimal planning strategy will be presented to maximize social welfare in the mentioned electricity market. Also, by presenting new indices, using hierarchical methods, and solving a two-level problem, all market participants' satisfaction will be maximized. The uncertainties are modeled by employing the Monte Carlo method, utilizing empirical cumulative density functions (ECDFs) derived from actual wind data. Furthermore, a reduction in computational burden will be achieved by employing a clustering algorithm that relies on the radial basis function neural network (RBFNN) to reduce the scenarios. The following is a summary of the paper's main contributions:

- Simultaneous consideration of the uncertainties of wind power plant and customers
- Involvement of participants with uncertainties in ancillary markets
- Maximizing producers and customers' satisfaction through novel economic indices and analytical hierarchical processes
- Development of strategies for optimal planning in day-ahead markets with locational marginal pricing mechanisms

The remainder of this paper can be divided into the following sections: Section 3 presents the problem formulation, section 4 conducts simulations to assess the performance of the presented approach, and section 5 provides the paper's conclusion.

2. Pricing mechanisms

In a competitive market where line congestion is a factor, two main approaches are utilized for estimating market prices [31]:

- Market clearing price (MCP) method: All buses are priced the same using the MCP technique, which is the market's clearing price.
- LMP method: With this strategy, bus prices may vary from one to the next. In fact, the cost incurred as a result of a 1 MW increase in a bus's consumption is its marginal cost. Different amounts of LMPs may be present in different buses as a result of the transmission system's technical limits and the marginal cost of power production.

In electricity markets with the LMP mechanism, producers sell their energy to independent system operator (ISO) based on their bus price, while buyers (customers) pay ISO to buy energy based on their bus price. This sales model has been implemented by numerous markets such as PJM, ERCOT and so on. So, in this research, the prices of the systems' buses are calculated using the LMP approach.

2.1 LMP mechanism

The social welfare can be described as the difference between the costs incurred by producers and the benefits received by consumers. It can be formulated as follows, with *B(D)* representing customer benefits and *C(P)* denoting producer costs [32]:

$$SocialWelfare = B(D) - C(P) \tag{1}$$

Considering the systems constraints, the social welfare is maximized by ISO, and consequently the electricity market clearing price is determined. In many instances, *B(D)* does not have a clear equation, and if it does, it will likely be highly complicated. As a result, the *B(D)* will be overlooked, and the objective function below is minimized [32]:

$$min\left(\sum_{i=1}^{np} C_i(P)\right) \tag{2}$$

In which:

$C_i(P)$: i^{th} power plant's cost function.

np: The number of power plants.

The aforementioned optimization problem can be more easily solved using the direct current optimal power flow (DCOPF) approach [33]. The equations for the DCOPF are derived by making the following simplifying assumptions [27, 28, 33-35]:

- The resistance of each branch, is negligible compared to the reactance. So, the admittance of each branch can be estimated as follows:

$$Z_{ij} = R_{ij} + X_{ij}\, j \approx X_{ij}\, j \rightarrow Y_{ij} = -\frac{1}{X_{ij}}\, j \tag{3}$$

- The magnitude of the voltage at every bus is equal to its nominal value ($|V|$=1)
- The changes in voltage angles along each branch are negligible enough to permit the following approximations:

$$\begin{aligned} &Cos(\delta_i - \delta_j) \approx 1 \\ &Sin(\delta_i - \delta_j) \approx \delta_i - \delta_j \end{aligned} \tag{4}$$

  In which δi and δj are voltage angles of i^{th} and j^{th} buses.

- Given these conditions, the flow of reactive power within the system is insignificant, and the net active power injections are linked to the bus voltage angles through the subsequent set of equations:

$$\begin{aligned} &P_i - P_{Di} = \sum_{j=1}^{n} |Y_{ij}| Cos(-90+\delta_j - \delta_i) = \sum_{j=1}^{n} |Y_{ij}| Cos(90-(\delta_i - \delta_j)) = \sum_{j=1}^{n} |Y_{ij}| Sin(\delta_i - \delta_j) \\ &\rightarrow P_i - P_{Di} = \sum_{j=1}^{n} |Y_{ij}| (\delta_i - \delta_j) \qquad i=1,\dots,n \end{aligned} \tag{5}$$

  In which P_i and P_{Di} are generated and consumed active power of bus number i, respectively.

- The power transmitted between nodes *i* and *j* is provided as follows:

$$P_{ij} = Y_{ij}(\delta_i - \delta_j) \quad j, i = 1, \dots, n \tag{6}$$

So, for each branch, the power limit can be stated as follows:

$$Y_{ij}(\delta_i - \delta_j) \leq P_{ij}^{max} \quad j, i = 1, \dots, n \tag{7}$$

Using equations (5)-(7), the Lagrangian function of the optimization problem (equation (2)) is derived as follows:

$$l = \sum_{i=1}^{n} C(I_i) + \sum_{i=1}^{n} \pi_i \left[I_i - \sum_{j=1}^{n} Y_{ij}(\theta_i - \theta_j) \right] + \sum_{i=1}^{n} \sum_{j=1}^{n} \mu_{ij} \left[P_{ij}^{max} - Y_{ij}(\theta_i - \theta_j) \right] \tag{8}$$

This equation comes from the KKT condition, where π_i, i=1,…,n denote the Lagrange multiplier associated with the i^{th} equality constraint, correspond to equations (5) and (6), and similarly μ_{ij} , i,j=1,…,n are the Lagrange multiplier correspond to the inequality constraint in equation (7) [36]. By computing partial derivatives of this function with respect to the relevant variables, the optimal conditions can be determined. Consequently, by taking the derivative of the Lagrangian function with respect to the net injected power at each bus, the market-clearing price for each bus (LMP), can be calculated in the following manner:

$$\frac{\partial l}{\partial I_i} = \frac{dC_i}{dI_i} - \pi_i = 0 \quad i = 1, \dots, n \tag{9}$$

In which π_i is equal to the LMP of i^{th} bus.

3. Problem formulation

Only conventional power plants with a certain level of production are taken into account in equation (2). As mentioned earlier, the existence of uncertainty in the energy generated by power plants or consumed by customers has impacts on LMPs, participant benefits and losses, and ultimately social welfare. So, the objective function should take these uncertainties into account. In other words, the market equilibrium will be changed if any of the participants deviates from its contracted amount because of its uncertainties. As a result, the approach provided below is used to determine the equilibrium point and LMPs considering these uncertainties:

Due to the fact that the normal and exponential distribution functions used in many studies to model participants' uncertainty are far from the participants' actual behavior, the ECDF curves will be used in this paper to model participants' uncertainty [37]. In order to achieve this, initially the ECDF curves for wind and uncertain customer are computed using their actual historical data. Then, 1000 scenarios for the wind farm and 1000 scenarios for the uncertain customer are generated using the obtained ECDF curves and 1000 random integers in the range [0 1]. Since there are 10^6 possibilities, the RBFNN clustering algorithm is employed to reduce them [38]. So that the probability density functions (PDFs) of the reduced scenarios behave like the original functions, this reduction is done. If this is the case, analysis can be done using the simplified scenarios and generalized to all circumstances. Using these simplified scenarios and the related PDFs, it is now possible to calculate the costs of deviation from contracted values as follows.

If the producer generates less energy than the contracted one, it must obtain the power shortage from the spot market. On the contrary, if the producer generates more energy than the contracted one, it can sell this excess energy on the spot market. Furthermore, as the amount of power is uncertain, the expected values of surplus costs or sale in the spot market must be calculated. If the contracted amount of wind power and its occurrence probability are assumed to be P_w and Pr_w, respectively, the expected value of the wind power plant's profit is obtained using the following equation:

$$Rev_{w,h} = P_{w,h} \times \pi_{w,h} \times Pr_{w,h} \tag{10}$$

In which:

h: time (hour).

Rev_w: Wind power plant's profit.

π_w: LMP of the bus where the wind power plant is connected.

If P_w is not produced at hour h, another power with the occurrence probability of $(1\text{-}Pr_w)$ is likely to be delivered. In this case, it is assumed that the average of the generated scenarios for wind power occurs. If this amount exceeds the contracted amount, the WPP can sell surplus amount by contributing in the spot market; else, it must get the lack of power from the spot market.

$$Cost_{Spot_{w,h}} = \begin{cases} 0 & if \;\; P_{w,h} \le P_{w\_average,h} \\ \left(P_{w,h} - P_{w\_average,h}\right) \times \left(1 - Pr_{w,h}\right) \times \pi_{spot,h} & if \;\; P_{w,h} > P_{w\_average,h} \end{cases} \tag{11}$$

$$Earn_{Spot_{w,h}} = \begin{cases} \left(P_{w\_average,h} - P_{w,h}\right) \times \left(1 - Pr_{w,h}\right) \times \pi_{spot,h} & if \;\; P_{w,h} \le P_{w\_average,h} \\ 0 & if \;\; P_{w,h} > P_{w\_average,h} \end{cases} \tag{12}$$

In which:

$P_{w\_average}$: Average of scenarios for wind power generation.

$Cost_{Spot_w}$: Incurred costs to provide the lack of power from the spot market.

$Earn_{Spot_w}$: Money earned by selling surplus power in the spot market.

The total expected costs imposed on the wind power plant can also be calculated using the following equation:

$$\Delta C_{Wind} = Cost_{Spot_{w,h}} - Earn_{Spot_{w,h}} \tag{13}$$

Likewise, if the uncertain customer's consumption exceeds the contracted amount, it must supply the excess energy consumption at a higher price on the spot market. If, on the other hand, it consumes less than it has bargained for, it can sell the excess power on the spot market. The declared costs and revenues can be calculated as follows:

$$Payment_{Spot_{L_i,h}} = \begin{cases} 0 & if\ P_{L_i,h} \geq P_{L_i\_average,h} \\ \left(P_{L_i\_average,h} - P_{L_i,h}\right) \times \left(1 - Pr_{L,h}\right) \times \pi_{spot,h} & if\ P_{L_i,h} < P_{L_i\_average,h} \end{cases} \tag{14}$$

$$Earn_{Spot_{L_i,h}} = \begin{cases} \left(P_{L_i,h} - P_{L_i\_average,h}\right) \times \left(1 - Pr_{L,h}\right) \times \pi_{spot,h} & if\ P_{L_i,h} \geq P_{L_i\_average,h} \\ 0 & if\ P_{L_i,h} < P_{L_i\_average,h} \end{cases} \tag{15}$$

In which:

P_{L_i} : Amount of uncertain customer's power consumption at bus number.

$P_{L_i\_average}$: Average of uncertain customer's power consumption scenarios.

Pr_L : Occurrence probability of the contracted power (P_{L_i}).

$Payment_{Spot_{L_i}}$: Uncertain customer's payment for providing the surplus power consumption power from the spot market.

$Earn_{Spot_{L_i}}$: Money earned by selling of the surplus contracted power in the spot market.

The total expected costs imposed on the uncertain customer can also be calculated using the following equation:

$$\Delta C_{Customer} = Payment_{Spot_{L_i,h}} - Earn_{Spot_{L_i,h}} \tag{16}$$

Considering the fact that each participant has a market power, his offer can affect the equilibrium point. Accordingly, the hypothesis of participation in the spot market, results in scheduling the participants considering their occurrence probability. This scheduling provides more benefits to the participants and stability to the network. On the other hand, in this case, the profit of each buyer or seller can be assigned in a way that, from their viewpoint, is not desirable. Indeed, the results of new scheduling for some participants may be worse than the old ones. Thus, in the second level of optimization problem, a number of economic indices are defined which are raised from concerns of the market stakeholders, to evaluate their satisfaction. The results of new planning can improve some of the mentioned indices more and others less, sometimes even bringing them closer to undesirable values. Here, the question arises whether the satisfaction of all market participants is the same? Therefore, the proposed indices are evaluated and prioritized using the Analytical Hierarchy Process (AHP) method and expert selection [39-41]. Two indices are used to make decision: the total cost of all power plants (TCP) and the total cost (payments) of all customers (TCC). TCP and TCC can be described as follows:

$$TCP=\left(\sum_{i=1}^{n} C_i\right)+\Delta C_{wind} \tag{17}$$

$$TCC=\left(\sum_{j=1}^{m} Payment_j\right)+\Delta C_{Customer} \tag{18}$$

n and m are equal to the number of conventional power plants and number of customers, respectively. In the following, based on buyer and seller experts viewpoints, importance coefficients are considered for each index. Now, by forming the decision matrix D and using the importance coefficients, the final decision matrix FD is obtained:

$$\begin{aligned} &D=[TCP \quad TCC] \\ &B=\begin{bmatrix} \beta_{1p} & \beta_{2p} \\ \beta_{1c} & \beta_{2c} \end{bmatrix} \\ &FD=B.D'=\begin{bmatrix} \beta_{1p} & \beta_{2p} \\ \beta_{1c} & \beta_{2c} \end{bmatrix}.\begin{bmatrix} TCP \\ TCC \end{bmatrix} \end{aligned} \tag{19}$$

In which:

B: Importance coefficient importance matrix.

Finally, by assigning importance coefficients to each expert's viewpoint and utilizing the AHP approach, ISO determines the final index [39, 42]. Assuming that ISO determines the final coefficients α_1 and α_2 for each of the sellers' and buyers' perspectives, respectively, the amount of the final index is presented as follows:

$$\begin{aligned} &FI=\left[\alpha_1 \quad \alpha_2\right].FD=\left[\alpha_1 \quad \alpha_2\right].\begin{bmatrix} \beta_{1p} & \beta_{2p} \\ \beta_{1c} & \beta_{2c} \end{bmatrix}.\begin{bmatrix} TCP \\ TCC \end{bmatrix} \\ &\Rightarrow FI=\alpha_1.\left(\beta_{1p}.TCP+\beta_{2p}.TCC\right)+\alpha_2.\left(\beta_{1c}.TCP+\beta_{2c}.TCC\right) \end{aligned} \tag{20}$$

FI is the final index includes the opinions of all market participants. It's important to emphasize that minimizing the final index corresponds to maximizing the satisfaction of all participants while considering their importance levels. Therefore, the problem at the second level revolves around minimizing the final index.

$$\underset{\text{subject to the first level}}{\min(FI)} = \underset{\text{subject to the first level}}{\min\left(\alpha_1.\left(\beta_{1p}.TCP+\beta_{2p}.TCC\right)+\alpha_2.\left(\beta_{1c}.TCP+\beta_{2c}.TCC\right)\right)} \tag{21}$$

In other words, decision-making and problem-solving at the first level should be done in a way that the equilibrium point that results at the second level maximizes the final index. According to equations (1)-(21), generally speaking, proposed optimization problem is non-convex. However, its lower level (equation (8)) is convex one. This problem can be solved by the following steps:

1. At first, the decision variables of equation (21), P_w and P_L, are generated randomly considering the constraints. These variables are continuous, scalar variables.
2. Then, the obtained variables of the previous level (upper level) are considered as the constant values and the convex optimization problem of this level, equation (8), is solved by determining the related decision variables including the amount of generated power (P_{Gi}) and voltage angle of each bus (δ_i). They are continuous, scalar, too. Solving the optimization problem of the lower level leads to deducing the LMPs.
3. Using the obtained LMPs, the objective function of the upper level, equation (21), is calculated and this process will be repeated by updating the decision variables of the lower level based on a Meta heuristic algorithm till the results converge to a number.

It should be noted that the optimum results provided by the Meta heuristic algorithm are not global and are very dependent to the first random generated amount for the decision variables (P_w and P_L). So, to find the best local optimum solution, the optimization problem should be solved 100 times and the objective function with the lowest amount will be considered as the best one. Figure 1 depicts the flowchart of the proposed method.

4. Simulation and results

In this section, to assess the effectiveness of the proposed method, an analysis will be conducted on a sample transmission system consisting of eight buses, as depicted in Figure 2 [5], under various scenarios. It should be noted that the cost function of power plants can be expressed in $C_i = a.P^2 + b.P + c$. Also, the information of the system is tabulated in Table 1 and Table 2. In first scenario, the market is run without considering the wind power plant (base scenario), and the values of LMPs, producers’ cost, producers’ income, producers’ revenue and customers’ payments are obtained. A similar process is performed by considering a certain amount of wind power (12 MW) at bus 2, and the values are recalculated (scenario 2). The results are presented in Figure 3 and Table 3-Table 5.

Figure 3 and Table 3 indicate that the existence of wind power lowers costs since it provides inexpensive energy, especially for expensive buses. In other words, in presence of the cheap energy resources, the profile of the

market’s price will be flattened. It is evident that with increasing wind power penetration level, the LMP values decrease and, in some cases, even become negative [5]. To investigate the effect of these changes on the participant's satisfaction, the obtained results of Table 4 and Table 5 are used. Based on the results presented in Table 4, in the absence of wind energy, it is clear that power plants' overall profit has a negative value. Considering the regular subsidies offered to energy suppliers, who are frequently owned by the government, this negative profit may be economically acceptable. However, the results reveal that with the presence of WPP, the total expenses for power plants reduced by 564.13$, and their total sales decreased by 208.13$. However, in contrast, their overall profit experienced a notable increase of 355.99$. This decrease shows that from the perspective of the buyers, WPP's presence is beneficial. WPP is therefore beneficial from the perspectives of energy cost and selling. Furthermore, as indicated in the results presented in Table 5, customers’ total payments made have also decreased by 367.59$. This reduction demonstrates that WPP's presence is advantageous from the buyers’ perspective.

As previously determined, the inclusion of wind power in the system is favorable from the perspectives of all stakeholders. However, its participation in the day-ahead electricity market poses challenges owing to the variability of its production. This also is the case to customers with fluctuating power demands. As outlined in the previous section, in order to analyze the impact of these uncertainties, the ECDFs of real wind data and uncertain customer power consumption are obtained and shown in Figure 4 and Figure 5. Subsequently, utilizing the curves obtained and generating 1000 random values within the [0 1] interval, 1000 scenarios are created for both the wind power and bus 8 customer data. Following this, the RBFNN clustering method is utilized to decrease the number of scenarios and compute their probability density functions. The outcomes for both the original scenarios and the reduced scenarios are illustrated in Figure 6 and Figure 7.

The behavior of the reduced scenarios is fairly similar to that of the main scenarios, according to Figure 6 and Figure 7. Consequently, market analysis can be conducted using the reduced scenarios. Subsequently, using these reduced scenarios and implementing the Monte Carlo method, the market is simulated, and the PDF values for the LMPs of bus 2 and bus 8 considered as the sample busses are determined. Additionally, PDFs for the TCP and the TCC are calculated, and the results are presented in Figure 8. Also, to analyze the efficiency of the scenario reduction process, the computational time of the problem solving is derived in two cases: with and without scenario reduction process. The results show that computational time is 72667.099 seconds before scenario reduction. In case of scenario reduction, based on RBFNN method, it reaches to 51.497 seconds. It can be concluded that scenario reduction can effectively reduce the computational burden and increase the speed of calculations. It should be noted that in this paper, all the simulations are implemented in MATLAB R2018b in a Core i3 PC with 3.5 GHz processing frequencies of CPU and 8 GB of RAM.

According to Figure 8, it is observed that the values are not definite, and there are a group of answers. It must be mentioned that each of these answers is probable. In the following, the expected value (average) of the results obtained for scenario 3 has been calculated and is displayed in Table 6. Also, for better comparison, the certain values of these parameters have been added to the second row of Table 6.

According to Table 6, it could be seen that the expected values are significantly different from the definite values, which should be taken into account in planning programs. To justify the significant difference between the expected and certain values of TCC and TCP, it's essential to consider the variance in input data and outputs. For instance, the variance of wind power and consumption of bus 8, derived from historical data, are 24.44 MW and 0.96 MW, respectively. Additionally, the variances of TCC and TCP are calculated to be 8547.02$ and 34681$, respectively. The discrepancies between the mean values of TCC (837.19$) and TCP (1427.40$) and their certain values can be attributed to the inherent market dynamics where each participant holds market power. Changes in production or demand from these participants lead to fluctuations in parameters such as energy prices and production costs. Given the high variance in input data, particularly from real measurements, alterations in wind power and uncertain demand from bus 8 inevitably result in significant changes in TCC and TCP. Therefore, the observed differences between the mean and certain values of TCC and TCP are justifiable within the context of market uncertainties and the complexities of real-world data. In summary, the substantial difference between expected and certain values of TCC and TCP can be explained by the variability in input data and the influence of market dynamics.

Next, utilizing Figure 8. a-d, the Empirical Complementary Cumulative Distribution Functions (ECCDF) for each of these parameters are derived. Using these ECCDFs, the occurrence probability of each specific parameter and its corresponding expected value are calculated. The ECCDF of the parameters and their occurrence probability are presented in Figure 9 and Table 7, respectively.

Based on the results obtained from Table 7, it is evident that at bus 2, the occurrence probability of a value equal to or exceeding the average price (40.69$/MWh) stands at 86.9 percent, indicating a satisfactory level of probability. To put it differently, the price at bus 2 is likely to be approximately 40.69$/MWh. Additionally, the probability that a particular price would occur and be less than a definite value is decreased to 54.4 percent. At bus 8, the occurrence probability of the definitive price and the average price will be close to each other and is approximately 16.7 percent. These results indicate that the price much higher than these values are expected for the bus 8.

Regarding the total payment, certain value will not happen undoubtedly (0 percent probability), which confirms the necessity of planning based on uncertain data. Also, the probability of payment equal to the calculated average value is low (22 percent). This means that customers will almost certainly pay significantly less than 837.19$ for energy purchases. Moreover, regarding the total cost of power generation by power plants, the probability of a certain value is higher than the average value. Therefore, costs higher than 1363.47$ are more probable.

The two criteria of total cost and total payment are crucial in making decisions, according to the proposed methodology in the preceding section. Consequently, the upcoming analysis will exclude price considerations and instead focus on investigating these two aforementioned parameters. Using the curves in Figure 9 and the assumption that 90 percent is a reliable probability for market decision-makers, the TCP and TCC are calculated to be 816.8 and 1204 dollars, respectively. Therefore, it is highly probable that values larger than or equal to these values are occurring values.

The study indicated above helps market players make more informed trading decisions by helping them better understand what will actually happen in the face of uncertainties. The aforementioned study suggests that while planning energy markets, market decision-makers should take wind and load uncertainties into account. Therefore, market planning is carried out using the techniques outlined in section 4 while taking into account potential scenarios for uncertainties, the related PDFs, and participation in the marginal market.

The energy price in the spot market, in accordance with equations (11)-(21), is an essential component for solving the proposed objective function. According to [5], it is set at 1.1 times the cost of the most expensive bus. The price of energy price in the spot market is necessary, according to, to solve the proposed objective function, and according to, it is 1.1 times the price of the most expensive bus.

$$\pi_{spot,h} = 1.1 \times max\left(\pi_{i,h}\right) \qquad i = 1,...,8 \tag{22}$$

Also, the importance coefficients matrix of the seller and buyer experts (B) to each of the TCP and TCC parameters and the importance coefficients matrix of ISO to each of these two experts (α) are assumed as follows:

$$B = \begin{bmatrix} \beta_{1p} & \beta_{2p} \\ \beta_{1c} & \beta_{2c} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

$$\alpha = \begin{bmatrix} \alpha_1 & \alpha_2 \end{bmatrix} = \begin{bmatrix} 0.33 & 0.67 \end{bmatrix}$$

Taking into account the aforementioned assumptions, the presented optimization problem is resolved through the utilization of the TLBO algorithm, as described [43-45]. This approach enables the scheduling of the market while accommodating uncertainties (scenario 4). This planning satisfies all the participants according to their importance level. The results are presented in Figure 10 and in Table 8-Table 10.

As depicted in Figure 10, the Locational Marginal Prices in the optimal scenario closely resemble those observed in the presence of certain wind power. This observation demonstrates the efficiency of the proposed method in flattening the price profile. In other words, as mentioned earlier, the presence of renewable energy such as wind power plants makes prices flatter, and the use of the proposed method has been effective in maintaining this positive feature.

To examine the results, it is essential to calculate the average values of the generated scenarios for both wind power and uncertain customer consumption. These averages amount to 13.31 MW for wind power and 14.9 MW for load power, respectively. According to the results of Table 8 and considering the averaged amounts, it can be understood that if the scheduled amount of WPP does not occur, its average amount will most likely occur. As a result, it will participate in the spot market to sell any excess power it produces. Similar to the above, if the planned amount of customer consumption does not happen, its average amount will most likely. Consequently, it will sell any excess energy it has bought on the spot market.

The results in Table 9 indicate that the total cost of power plants has decreased by 112.73$ when compared to the base scenario, which is desirable for sellers. The results of show that the total cost of power plants has been reduced by 112.73$ compared to the base scenario, which is favorable for sellers. However, it performs worse than scenario 2 in terms of reducing the total cost. From the selling of energy’s viewpoint, the total sell has been increased by 212.72$ and 420.85$ compared to the scenarios 1 and 2, respectively, which is desirable from the sellers' perspective. Finally, from the profit's viewpoint, it is determined that the total profit has increased by 362.03$ and 6.04$ compared to the scenarios 1 and 2, respectively. These results indicate the satisfaction of energy sellers.

As mentioned before, in the presence of the wind power (scenario 2), the amount of payments have been considerably reduced, which is favorable for buyers. Table 10’s results show that employing the proposed strategy yields outcomes that are comparable to those of scenario 2, which satisfy customers. In this case, compared to scenarios 1 and 2, the total payment has been reduced by 928.39$ and 560.8$, respectively. This reduction will be equal to the profit of the customers. For better comparison, the variations in the TCP, the total sell, the total revenue of all power plants (TRP), and TCC the total payment of the buyers are depicted in Figure 11.

The above results validate the effectiveness of the proposed approach in improving the parameters in comparison to the two base and certain wind power scenarios. Only in the terms of the total cost, the proposed method slightly increases compared to the certain wind power scenario, which will also be acceptable given the improvement in the total revenue and the satisfaction of all market participants. Now, let's assume that the scheduled amounts of wind and customer power occur the following day at the designated time, as in scenario 4. In another scenario (scenario 5), the parameters are recalculated, assuming that the scheduled amounts for the uncertain participants did not occur. Instead, their expected value (average) has occurred. By comparing the values obtained in these two cases with the base case, the upper and lower limits of TCP and TCC can be obtained. The obtained results are shown in Table 11.

The results of Table 11 imply that in each of the scenarios 4 and 5, the satisfaction of market participants is obtained by improving the TCP and TCC parameters. If the planned values occur, the minimum values for the mentioned parameters will be obtained, and if the planned values do not occur, the amount of the mentioned parameters and, consequently, the participants' satisfaction can be increased up to the maximum value. Realistically, as given in Table 11, the average values of the parameters can be imagined for each of the buyer and seller participants. The boxplot of the TCP, TCC and wind sell can be found in Figure 12.

Finally, to evaluate the performance of the proposed method in comparison with existing methods, the total revenue of the power plants and customers are calculated under strategies given in this paper and in [5]. The obtained results under these methods are tabulated in Table 12. It should be noted that the total revenue of customers is actually the difference of their total payment in the base scenario compared to the optimal scenario.

The results of Table 12 show that under the proposed method the power plants' total revenue is increased by 275.18$ compared to result of [5]. Also, the customers' total revenue is increased by 10.35$. So, it is inferred that the proposed method improves the amount of social welfare (total benefits of customers and power plants owners) by 285.83$. It is worth to mention that all the above studies have been done just for one hour. Therefore, if it is implemented during a day, and accordingly during a year, the obtained benefits will be considerable.

5. Conclusion

This study presents an innovative approach to optimize social welfare in the day-ahead electricity market, taking into account uncertainties associated with wind power plants and customer consumption. This approach integrates critical components, including the Locational Marginal Price (LMP) mechanism, participation in the spot market, and coefficients representing the importance of market participants. Additionally, it employs the Monte Carlo method and Empirical Cumulative Distribution Functions (ECDFs) to model uncertainties among participants.

Two indices have been introduced to evaluate the satisfaction of power market stakeholders. The approach was applied to an 8-bus sample transmission system, utilizing real data for wind power producers and customers. The findings demonstrate that, when uncertainties are not considered, wind power has the potential to reduce LMPs. Moreover, it results in a total cost reduction of 564.13$ for power plants and a decrease in the total payment made by customers by 367.59$ compared to the base scenario. However, a probabilistic analysis has revealed that the occurrence of a specific level of wind power and the associated advantages were unlikely. Thus, by utilizing the proposed methodology, uncertain participants engaged in the electricity market to optimize the values of the mentioned indices. In this scenario, the total cost for power plants reduced by 112.73$, and customers' total payment decreased by 928.39$ compared to the base scenario. Taking into account these outcomes and the assessment of various economic parameters, such as total profits, it is evident that the proposed methodology is effective. To conclude, based on the results obtained from the presented method, the expected ranges for total cost fall between 1,270.91$ and 1,719.50$, while the expected ranges for total payment range from 2,151.41$ to 2,192.58$.

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Figures:

Figure 1. Flowchart of the proposed method

Figure 2. Sample transmission system

Figure 3. Transmission network's LMPs with and without WPP

Figure 4. ECDF curve for wind power

Figure 5. ECDF curve for uncertain customer

Figure 6. Histogram and probability density function curves for wind power scenarios

Figure 7. Histogram and probability density function curves for uncertain customer scenarios

Figure 8. Probability density function curves subsequent to the implementation of Monte Carlo method (a: LMP_{Bus2} b: LMP_{Bus8} c: TCP d: TCC)

Figure 9. ECCDF curves subsequent to the implementation of Monte Carlo method (a: LMP_{Bus2} b: LMP_{Bus8} c: TCP d: TCC)

Figure 10. LMPs subsequent to the implementation of the proposed method

Figure 11. Changes in economic parameters subsequent to the implementation of the proposed method

Figure 12. The range of variability in TCC, TCP, and wind power sell taking into account the outcomes of the proposed approach

Tables:

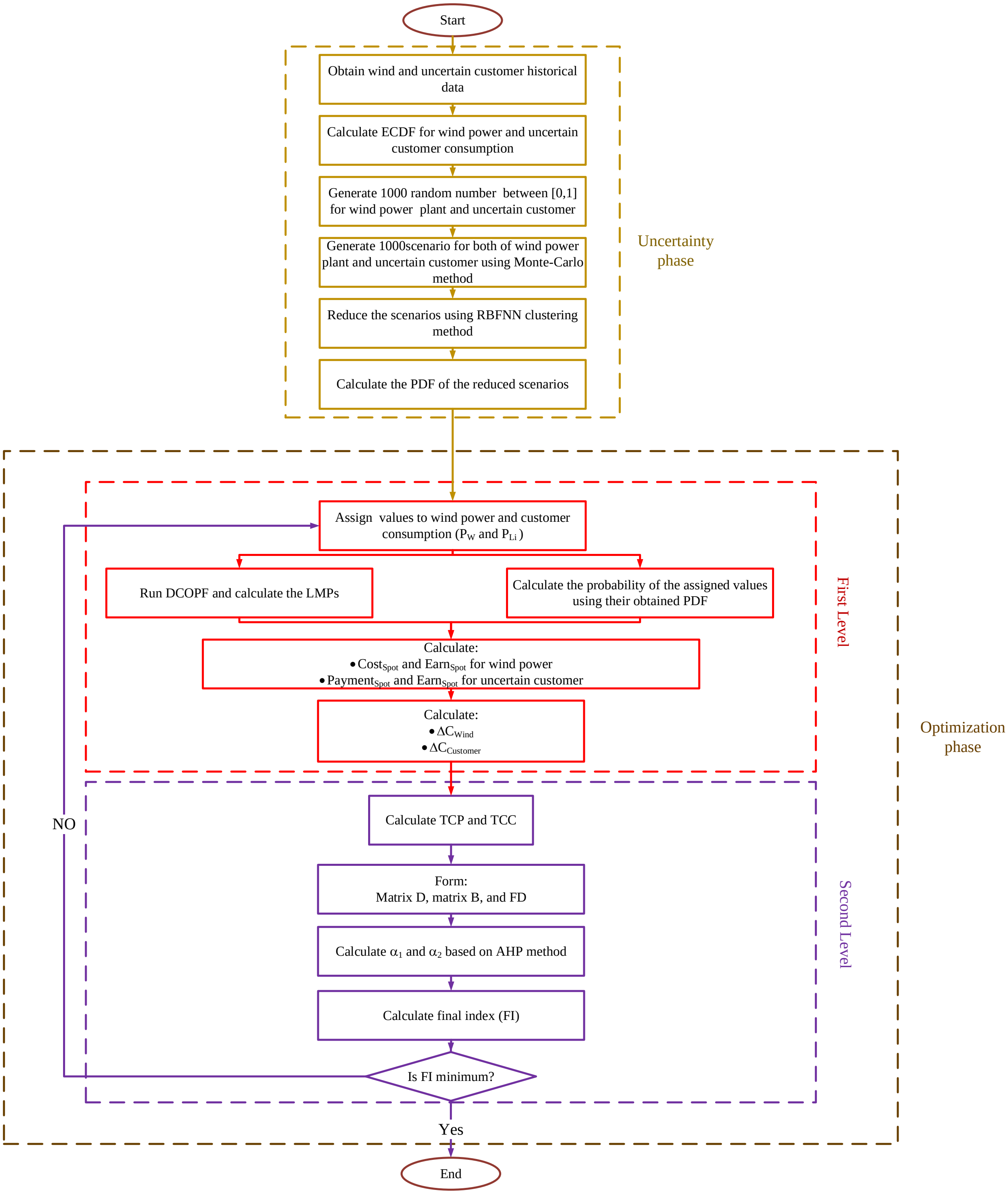
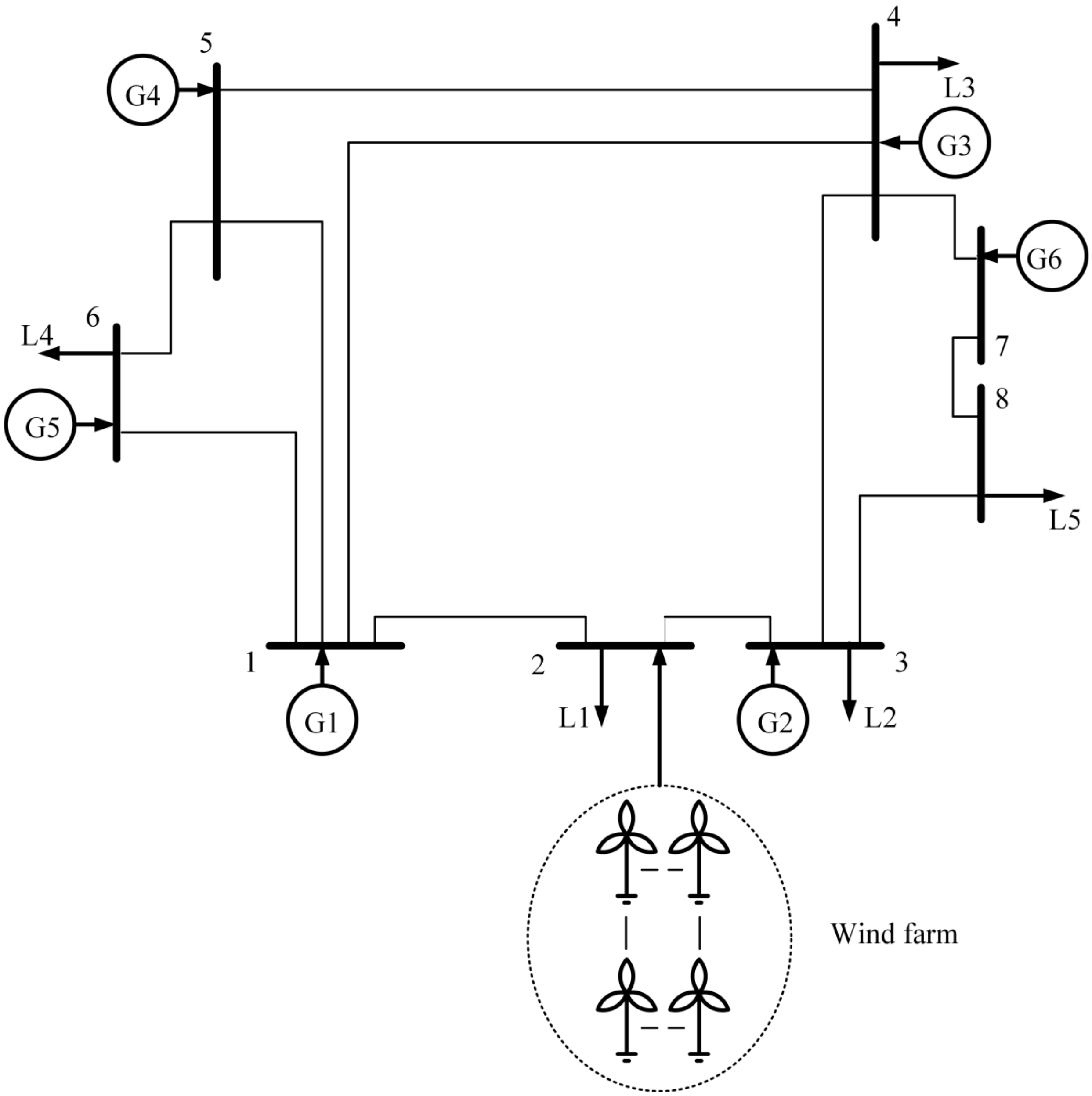

Start
Obtain wind and uncertain customer historical data
Calculate ECDF for wind power and uncertain customer consumption
Generate 1000 random number between [0,1] for wind power plant and uncertain customer
Generate 1000scenario for both of wind power plant and uncertain customer using Monte-Carlo method
Reduce the scenarios using RBFNN clustering method
Calculate the PDF of the reduced scenarios
Uncertainty phase
Assign values to wind power and customer consumption (P_W and P_{Li})
Run DCOPF and calculate the LMPs
Calculate the probability of the assigned values using their obtained PDF
Calculate:
• $Cost_{Spot}$ and $Earn_{Spot}$ for wind power
• $Payment_{Spot}$ and $Earn_{Spot}$ for uncertain customer
Calculate:
• ΔC_{Wind}
• $\Delta C_{Customer}$
First Level
Optimization phase
NO
Calculate TCP and TCC
Form:
Matrix D, matrix B, and FD
Calculate α_1 and α_2 based on AHP method
Calculate final index (FI)
Is FI minimum?
Second Level
Yes
End

Figure 1.



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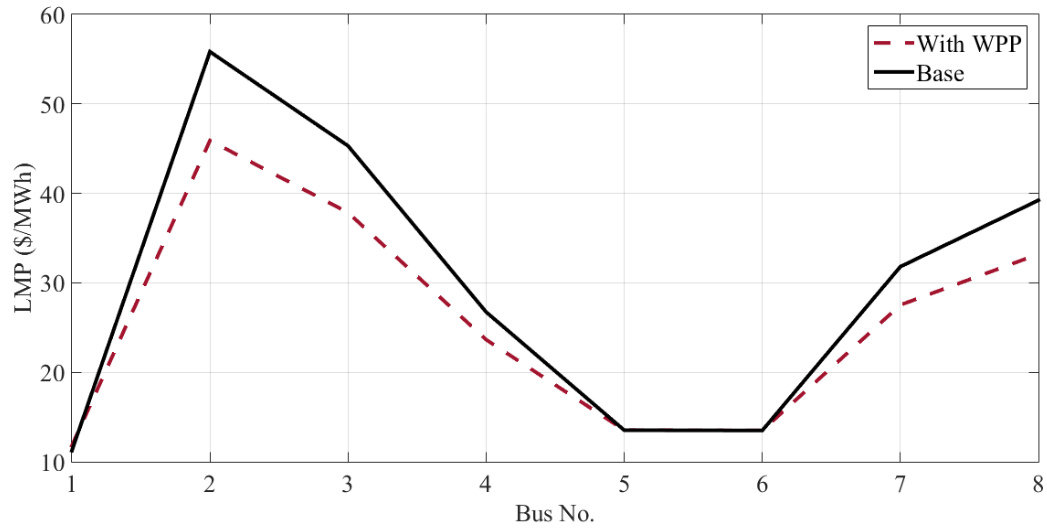

Figure 3.

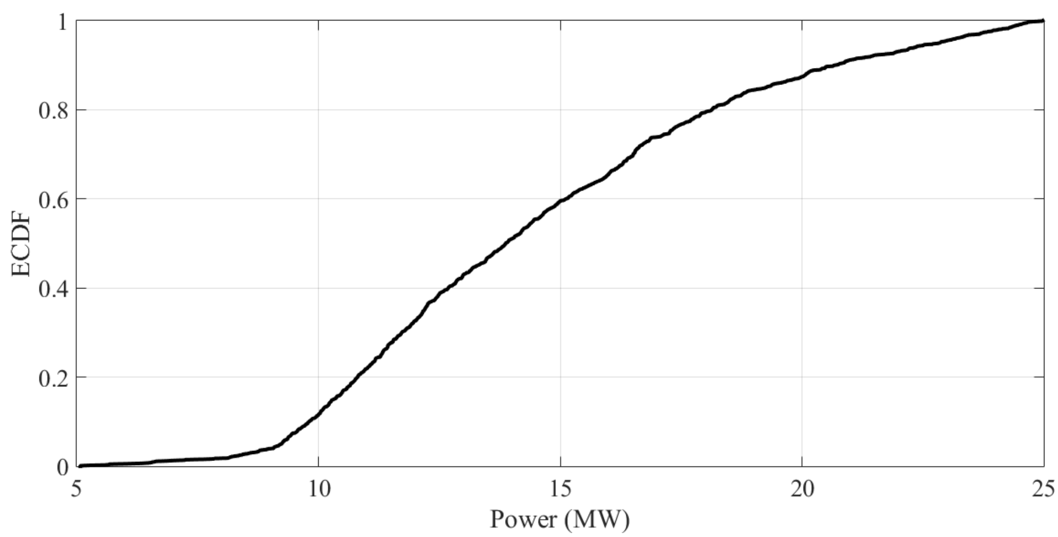

Figure 4.

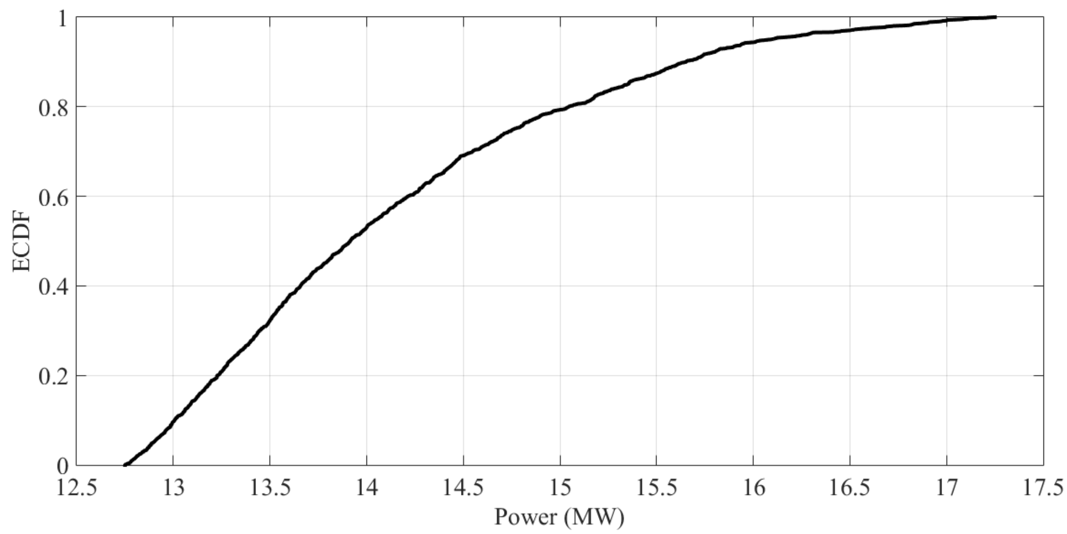

Figure 5.

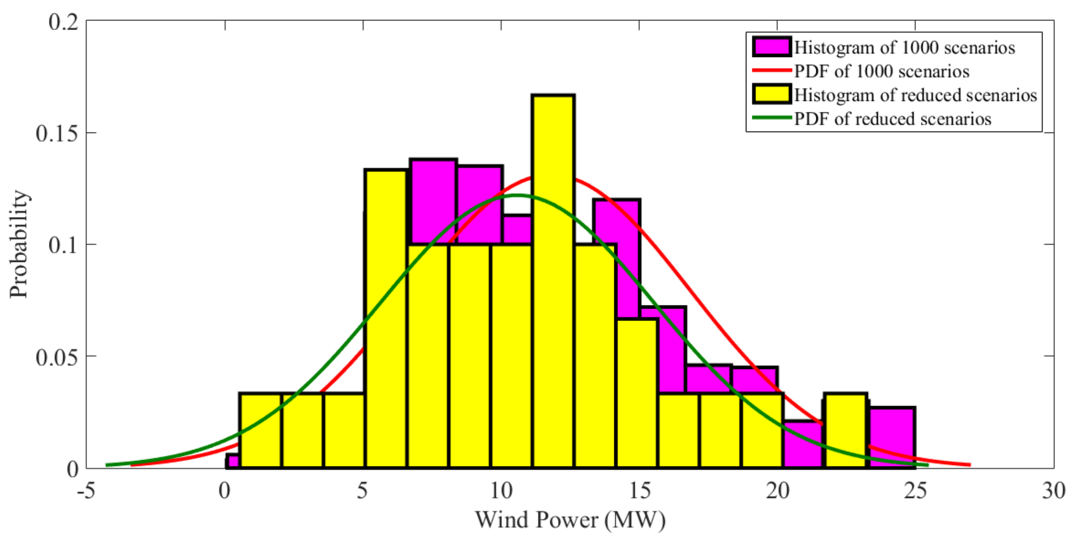

Figure 6.

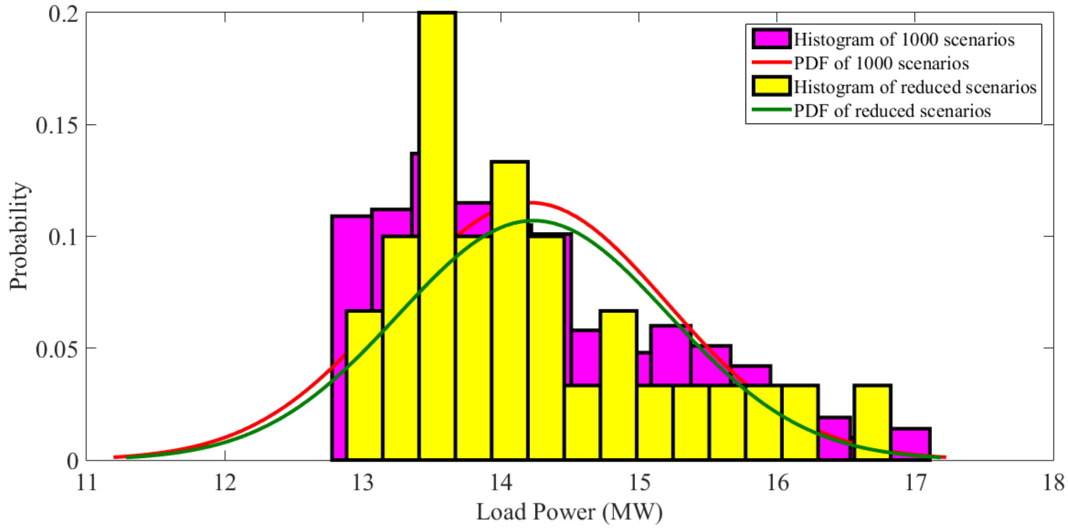

Figure 7.

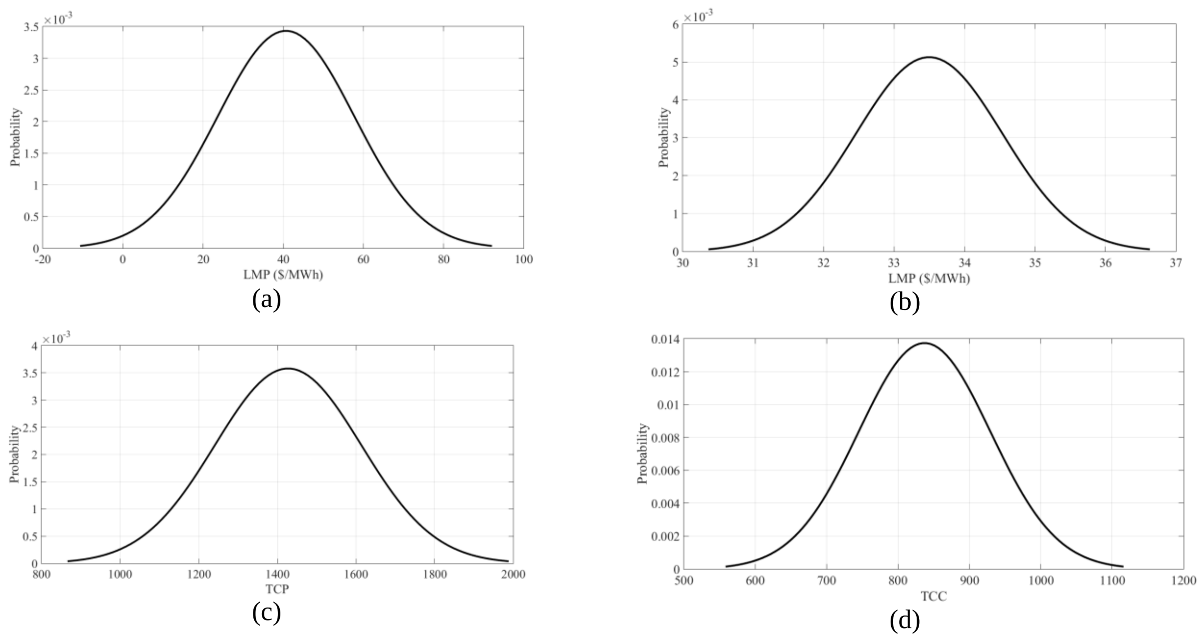

Figure 8.

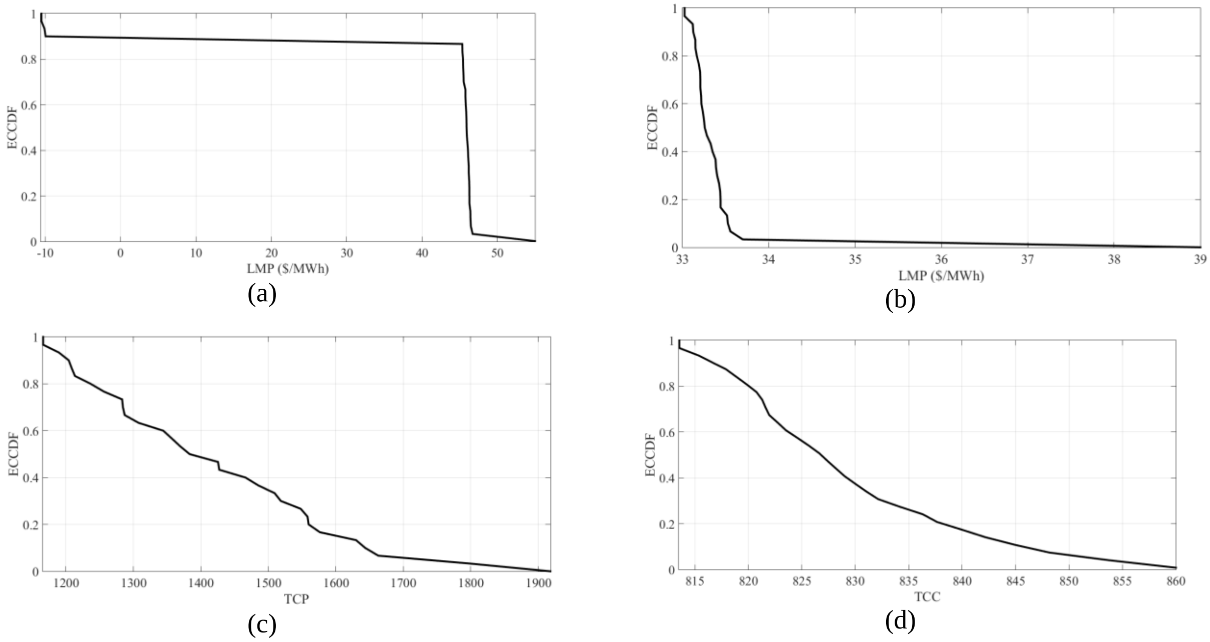

Figure 9.

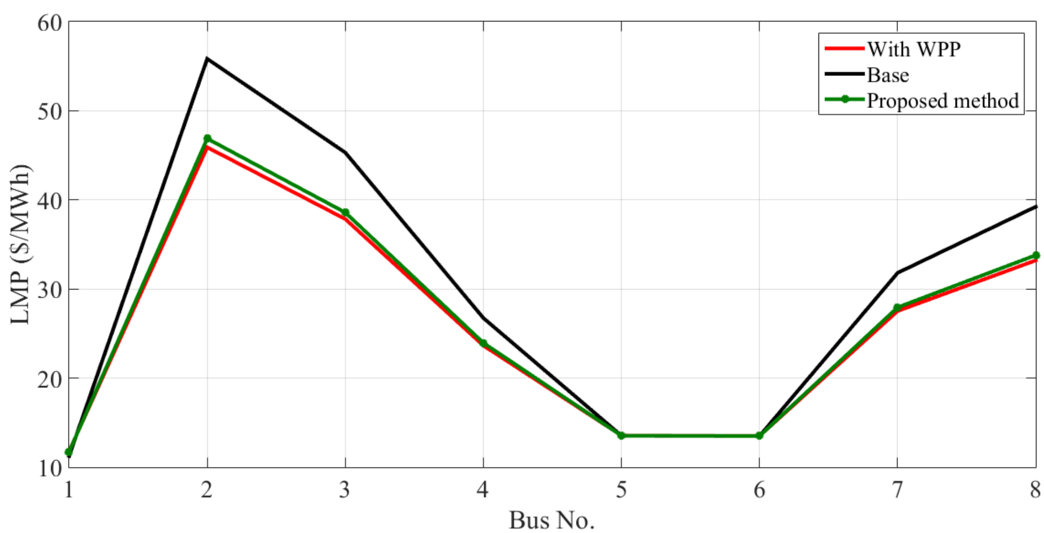

Figure 10.

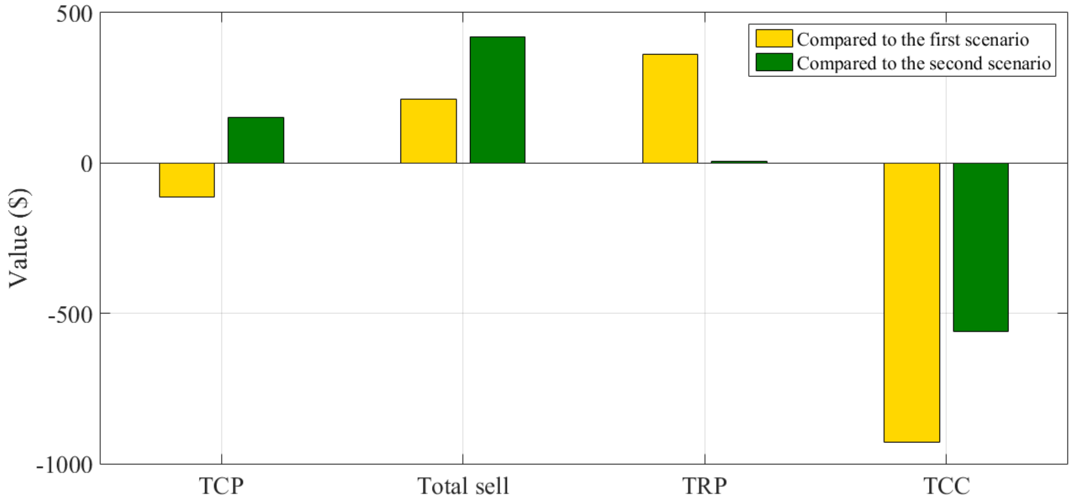

Figure 11.

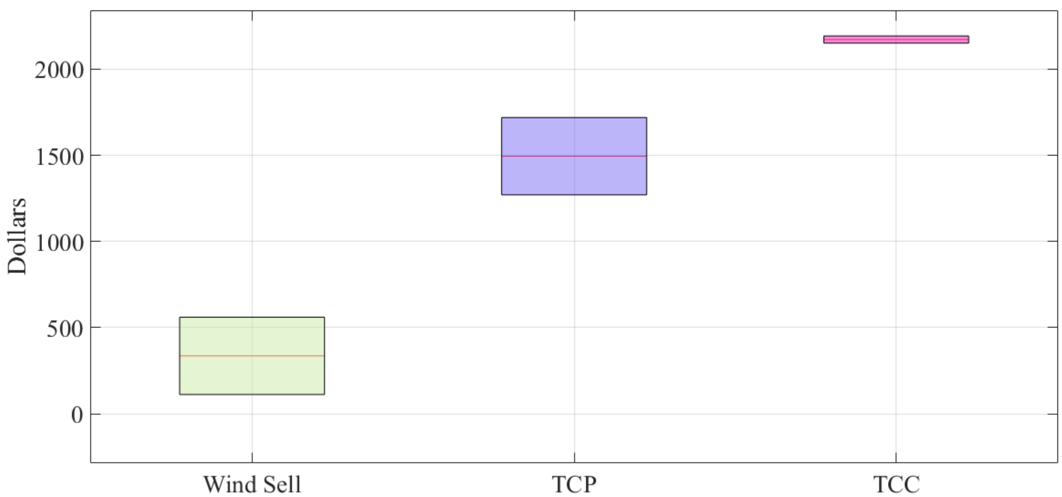

Figure 12.

Table 1.

Bus	a ($/MWh^2)	b ($/MWh)	C ($/h)	P_{min} (MW)	P_{max} (MW)	Pd (MW)
1	0.0048193	14.37181	89.62	0	35	0
2	0	0	0	0	0	15
3	0.0245283	37.60189	17.64	0	20	11
4	0.0730337	26.34562	31.6	0	32	15
5	0.002	13.39	79.78	0	40	0
6	0.01	13.47	49.75	0	20	15
7	0.05	25.47	24.05	0	12	0
8	0	0	0	0	0	15

Table 2.

Line	From Bus	To Bus	Reactance (p.u.)	Limit (MW)
1	1	2	0.03	9
2	1	4	0.03	15
3	1	5	0.0065	20
4	2	3	0.011	10
5	3	4	0.03	10
6	4	5	0.03	20
7	5	6	0.02	10
8	6	1	0.025	19
9	7	4	0.015	19
10	7	8	0.022	20
11	8	3	0.018	15

Table 3.

Bus	LMP ($/MWh)	
	Base	With WPP
1	11.25	11.80
2	55.83	45.90
3	45.31	37.85
4	26.74	23.65
5	13.53	13.55
6	13.50	13.51
7	31.81	27.53
8	39.23	33.21

Table 4.

	Cost ($)		Sell ($)		Revenue	
	Base	With WPP	Base	With WPP	Base	With WPP
Total	1927.6	1363.47	1851.34	1643.21	-76.25	279.74

Table 5.

	Payment ($)	
	Base	With WPP
Total	2528.04	2160.45

Table 6.

Scenario	$LMP_{@BUS2}$ ($/MWh)	$LMP_{@BUS8}$ ($/MWh)	TCC($)	TCP ($)
EV*	40.69	33.50	837.19	1427.40
CV**	45.90	33.21	2160.45	1363.47

*Expected value (scenario 3)
**Certain value (scenario 2)

Table 7.

	$LMP_{@BUS2}$ ($/MWh)		$LMP_{@BUS8}$ ($/MWh)		TCC ($)		TCP ($)	
	EV	CV	EV	CV	EV	CV	EV	CV
ECCDF (%)	86.90	54.40	16.70	16.80	22.00	0	43.30	54.90

Table 8.

	$Customer_{@BUS8}$	WPP
Power (MW)	15.7	2.4

Table 9.

	Cost ($)			Sell ($)			Revenue ($)		
	Base	With WPP	Optimal scheduling	Base	With WPP	Optimal scheduling	Base	With WPP	Optimal scheduling
Total	1927.6	1363.47	1814.87	1851.34	1643.21	2064.06	-76.25	279.74	285.78

Table 10.

	Payment ($)		
	Base	With WPP	Optimal scheduling
Total	2528.04	2160.45	1599.65

Table 11.

Parameters	$Wind_{@BUS2}$=2.4MW $Load_{@BUS8}$=15.7MW	$Wind_{@BUS2}$=13.31MW $Load_{@BUS8}$=14.9 MW	Average	Variations compared to the base scenario	
				Min	Max
Wind sell ($)	112.27	560.86	336.56	112.27	560.86
TCP ($)	1719.5	1270.91	1495.2	-656.68	-208.09
TCC ($)	2192.58	2151.41	2171.99	-376.63	-335.46

Table 12.

	[5]	This study
Total revenue of power plants	10.6	285.78
Total revenue of customers	918.04	928.39

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