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Real time probabilistic power system state estimation

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ABSTRACT

Smartening of contemporaneous power delivery systems in conjunction with the increased penetration of renewable energies (REs), change the way to energize consumers who are willing to maximize their utility from energy consumption. However, there is a high degree of uncertainty in the electricity markets of such systems. Moreover, the unprecedented ascending penetration of distributed energy resources (DERs) mainly harvesting REs is a direct consequence of environmentally friendly concerns. This type of energy resources brings about more uncertainties into power system operation resulting in, necessitates probabilistic analysis of the system performance. In the smarter power markets, encountered the restructuring and deregulation, the online studies of system performance is of huge interest. This paper proposes a new methodology for real time state estimation, e.g. energy pricing by probabilistic optimal power flow (P-OPF) studies using the concept of hybrid artificial neural networks (ANN) and differential evolutionary (DE) method. In order to examine the effectiveness and applicability of the proposed method, two case studies are conducted and the obtained results are compared against those of Monte Carlo simulation (MCS) technique. Comparison of the results reveals the impressiveness of the method regards to both accuracy and execution time criteria.

Introduction

Uninterrupted variations of the energy consumption together with the integration of a significant amount of renewable energies (REs) such as wind and solar into the power networks bring about crucial operational challenges which stem from their inherent uncertainties. Real time pricing (RTP) is an effective mechanism used to manage the smart grids. If real time tariff of electricity is available in any time interval, consumers can react to this control signal and manage their energy costs. Optimal power flow (OPF) computation which can determine energy price at the system nodes, is one of the major requirements in power system planning and operation. Bare in mind that in such a highly uncertain and complex system, a deterministic OPF cannot reveal the state of system accurately; therefore, probabilistic studies are of significant importance. Deterministic OPF study requires specific values for all input variables such as loads, generation, and network conditions. In practice, modern power systems contain intermittent and variable energy resources like REs and therefore, the OPF uncertainty in such systems is not a minor subject, moreover, its real time application is another obligation. Performing P-OPF study helps the system planning engineers in making judgments concerning new investments by providing a better sense of future system conditions.

Generally, the term smart grid implies a fully automated electric power grid, controlling and optimizing operation of all its mutually connected segments, in order to warrant efficient operations of all energy generation, transmission and distribution facilities [1,2]. Note that the smart grids exhibits particular encouraging characteristics, e.g. demand side management (DSM) [3] and vehicle to grid (V2G) systems [4,5] among the rest. These capabilities yield notable benefits, e.g. enabling infrastructures for integrating large amounts of REs and installing distributed generation [6], new energy services and energy efficiency improvements [7]. Real time pricing of electricity in presence of different kind of uncertainties is of the major requirements for smart grid operation according to which electricity prices change frequently to represent variations in the cost of energy delivered [8]. Hence, this work mostly focuses on this issue and attempts to propose an appropriate technique to resolve this concern.

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Nomenclature

D	index of load
G	index of generation
C_w	weibull scale parameter (m/s)
K_w	weibull shape parameter
NG	population size of DE
$P^i_{\max}$	maximum allowable limit of active power generated by unit i (p.u.)
$P^i_{\min}$	minimum allowable limit of active power generated by unit i (p.u.)
P^i_{net}	net of active power injection at bus i (p.u.)
$\mathbf{P_D}$	vector of loads active power (p.u.)
$\mathbf{P_G}$	vector of generators active power (p.u.)
P_r	WTG rated power (p.u.)
$\mathbf{P}_{wind}$	vector of wind farms power generation (p.u.)
P_{WTG}	WTG output power (p.u.)
$\mathbf{Q_D}$	vector of load reactive power (p.u.)
$\mathbf{Q_G}$	vector of generators reactive power (p.u.)
$\mathbf{Q}_{wind}$	vector of wind farms reactive power consumption/generation (p.u.)
$Q^i_{\max}$	maximum allowable limit of reactive power generation by unit i (p.u.)
$Q^i_{\min}$	minimum allowable limit of reactive power generation by unit i (p.u.)
Q^i_{net}	net of reactive power injection at bus i (p.u.)
S^{ij}	the line power flow between buses i and j (p.u.)
$S^{ij}_{\max}$	maximum allowable limit of line power flow between buses i, j (p.u.)
TC	total operation cost of the power system ($)
v	wind speed (m/s)
$\mathbf{V}$	vector of bus voltage magnitude (p.u.)
$V^i_{\max}$	maximum allowable limit of voltage at bus i (p.u.)
$V^i_{\min}$	minimum allowable limit of voltage at bus i (p.u.)
v_i	wind turbine cut- in speed (m/s)
v_o	wind turbine cut- out speed (m/s)
v_r	wind turbine rated speed (m/s)
$\mathbf{X}$	vector of uncertain input variables
$X_{best,g}$	best individual at generation g of DE
$X_{i,g}$	the ith individual at generation g of DE
$X_{r,g}$	random individual at generation g of DE
Y_{ij}	admittance between buses i, j (p.u.)
$\mathbf{Y}$	vector of uncertain output variables
μ	mean value of normal distribution
σ	standard deviation of normal distribution
δ	vector of bus voltage angles (rad)
δ_i	voltage angle at bus i (rad)
θ_{ij}	angle of Y_{ij} (rad)

Beginning with the uncertainty, to comprehend the engineering system uncertainties, probabilistic approaches have been used since the early seventies [9,10]. As yet, many probabilistic methods have been developed to study the uncertainty associated with engineering systems. These methods generally can be classified into two categories: simulation and analytical methods. Monte Carlo simulation (MCS) is the widely used simulation method. MCS provides more accurate results but its execution might be extremely time-demanding, which degrades its appeal in real time applications. In order to reduce the computational burden, analytical methods were proposed. The summary of the reviewed literature is as follows. The problem of economic dispatch was considered as a probabilistic problem in [11], where the authors used Gram–Charlier series to represent the probability density function (PDF) of the system uncertain loads. Based on the same Gram–Charlier series technique, a more general approach to account the uncertainties associated with all OPF variables was proposed in [12]. The first-order second-moment method (FOSMM) is found on the basis of the first order Taylor series expansion [12]. The fuzzy theory was used in [13] to consider the load uncertainty in the OPF problem. The MCS method was used in [14] to analyze the OPF under the uncertainty in the forecasted load. In [15,16], the authors developed a new approach in probabilistic studies based on the point estimation method (PEM). The two point estimation method (2PEM) was proposed to P-OPF study in [17], which can obtain the results with an acceptable level of accuracy.

The main advantage of the analytical methods mentioned above is to avoid the cumbersome computer simulations. In contrast, these techniques impose more assumptions and complex mathematical algorithms [18].

For some analytical methods such as 2PEM, the execution time is either proportional or exponential with respect to the number of uncertain variables. This can diminish the superiority of these methods against simulation ones when the system dimensions become larger and larger. So, their usage in real time applications is impractical in these systems. None of the currently used methods can generalize its solutions to new conditions. This indicates that under any new conditions, the problem must be solved again resulting in a very time consuming procedure. To overcome such disadvantages, new analytical methods for probabilistic nonlinear systems are exceedingly necessary, which must have the following properties:

1. An acceptable level of accuracy.
2. Reasonable execution time which is not strongly dependent on the number of uncertain variables.
3. Easy to implement.
4. Capable of adaptation with the new conditions.
5. Applicable to real time applications.

These requirements can be achieved using the methods based on intelligence system such as the artificial neural networks (ANN) that essentially simulate the human brain behavior. ANN has been frequently used in recent years in different power system applications such as load forecasting [19,20], electricity price forecasting [21], wind speed forecasting [22], and state estimation in distribution system [23]. Note that the state estimation under the uncertainty in distribution systems may be more difficult because of their radial architecture, less observability, and low bulk effect, especially at the LV level.

However, based on the authors' best knowledge, there is no reported work about online P-OPF studies using the ANN and this illustrates the novelty of this work. The main contribution of this paper is to develop a new approach for real time energy pricing by performing online P-OPF studies using the concept of ANN. The proposed method can overcome drawbacks associated with the currently used probabilistic methods, from the simulation to the analytical approaches, and opens a new horizon in this context. The developed approach is online, has the adaptation capability and a high degree of accuracy, which will be shown in the following. At commence, the proposed method is introduced; thereafter, it is implemented in the online power system P-OPF study taking into account the uncertainties associated with the forecasted load and wind power generation. In the following, the proposed method is applied to a 6-bus and 30-bus test systems and then, the obtained results are compared with the MCS results with regards to both accuracy and execution time.

The rest of the paper is organized as follows. Section 'Optimal power flow problem' introduces the OPF, the P-OPF formulation, and some P-OPF methods. Section 'Uncertainty in OPF problem' discusses about the uncertainties associated with the OPF problem and their modeling. In Section 'Artificial neural network (ANN)', an introduction to ANN is presented; then, the proposed model is described and implemented to the P-OPF study. Section 'Case studies and discussion' describes the case studies; afterwards, the obtained results pertained to each case study are presented. The conclusion is drawn in Section 'Conclusion'.

Optimal power flow problem

Fundamentally, OPF is an optimization problem, generally operation cost minimization [24], which will be the objective function of this paper as well.

Optimal power flow formulation

Mathematically, the OPF problem can be formulated as the following constrained nonlinear optimization problem.

$$\begin{aligned} &Min. \quad TC(x,u) \\ &subject\ to \quad g(x,u)=0 \\ &\qquad f(x,u)\leqslant 0 \end{aligned} \tag{1}$$

The objective function $TC(x, u)$ is a scalar function. There are two types of variables in this optimization problem, state and control variables. x is a set of state variables ($\mathbf{V}$, δ) and u is a set of control variables (e.g. $\mathbf{P_G}$, $\mathbf{Q_G}$) [24]. The set of constraints can be divided into two categories of equality and inequality constraints. The equality constraints are power balance equations at each bus.

$$P_{net}^i=\sum_G P_i^G-\sum_D P_i^D \tag{2}$$

$$Q_{net}^i=\sum_G Q_i^G-\sum_D Q_i^D \tag{3}$$

$$P_{net}^i=|V_i|\sum_{j=1}^{N_b}|Y_{ij}||V_j|\cos(\delta_i-\delta_j-\theta_{ij}) \tag{4}$$

$$Q_{net}^i=|V_i|\sum_{j=1}^{N_b}|Y_{ij}||V_j|\sin(\delta_i-\delta_j-\theta_{ij}) \tag{5}$$

The inequality constraints include the upper and lower limits for bus voltages, active and reactive power generation of each unit, and transmission lines flows expressed as (6)–(9):

$$\left|V_{\min}^i\right|\leqslant\left|V^i\right|\leqslant\left|V_{\max}^i\right| \tag{6}$$

$$P_{\min}^i\leqslant P^i\leqslant P_{\max}^i \tag{7}$$

$$Q_{\min}^i\leqslant Q^i\leqslant Q_{\max}^i \tag{8}$$

$$\left|S^{ij}\right|\leqslant S_{\max}^{ij} \tag{9}$$

Probabilistic optimal power flow formulation

Power systems are inherently uncertain systems. Hence, in the P-OPF study, it is aimed to determine the state of the system as a function of uncertain input variables which can be stated as:

$$\mathbf{Y}=f(\mathbf{X}) \tag{10}$$

Input vector $\mathbf{X}$ is written as:

$$\mathbf{X}=[\mathbf{P_D}\,\mathbf{Q_D}\,\mathbf{P}_{DER}\,\mathbf{Q}_{DER}\,\ldots]^T \tag{11}$$

The input vector contains the load, the network conditions, the states of generating units and the power generated by the distributed energy resources (DERs) such as wind farms and solar farms among the rest. The output vector $\mathbf{Y}$ is stated as:

$$\mathbf{Y}=[\mathbf{V}\,\delta\,\mathbf{P_G}\,\mathbf{Q_G}_{\ldots}]^T \tag{12}$$

The uncertainty associated with input variables, influences the system state variables (e.g. $\mathbf{V}$, δ) as well as the system control variables (e.g. $\mathbf{P_G}$, $\mathbf{Q_G}$). Whereas, the output variables are related to both uncertain state and control variables, they also have their specific uncertainties.

Probabilistic methods

Probabilistic analysis of power system performance was first proposed in the early seventies [9]. So far, many probabilistic techniques have been developed which can be categorized into two main groups: Simulation methods like MCS and Analytical methods such as 2PEM.

Simulation methods are techniques that involve using random numbers and probability in order to solve the problems having uncertainties in their parameters. These methods suffer from the cumbersome computational burden. Analytical methods were proposed to avoid the cumbersome computational burden associated with simulation approaches by decreasing the number of problem evaluations but some simplifications and more complex algorithms are necessary. Interested readers are referred to [25], in which more explanations about these methods are provided.

Uncertainty in OPF problem

As discussed earlier, the uncertainty associated with power system parameters is not a negligible issue. This section briefly introduces some of the power system uncertain parameters and their modeling.

Uncertain parameters

The power industry deregulation and privatization cause that more and more uncertainties emerge in the system operation. OPF is often recognized as a deterministic optimization problem with fixed model parameters and input variables. However, many random disturbances or uncertain factors exist within the power system operation. These uncertainties impose errors in the OPF solutions when deterministic data is used; therefore, probabilistic analysis must be performed. Though, power systems are faced with variety of uncertainties, we mostly focus on uncertainties associated with the load, and wind power generation.

Uncertainty modeling

One of the most conspicuous and ubiquitous power system uncertainties stem from the load level ambiguity. It fluctuates as a function of time, weather conditions, and electricity price among the rest. Generally, load forecast is assumed to be normally distributed with forecasted load as the mean μ and the standard deviation (STD) equals to a fraction of the mean [26].

In order to model the wind power generation uncertainty, some buses are assumed to have integrated wind farms with uncertain output powers as a result of wind speed uncertainty. Wind speed varies both in time and location and its PDF is claimed to be weibull in the respected literature [27]. The WTG's output power uncertainty modeling is summarized as follow:

Step 1: Wind speed is modeled by an appropriate PDF such as weibull which is represented by (13).

$$f(v) = \frac{K_w}{C_w}\left(\frac{v}{C_w}\right)^{K_w-1} \exp\left[-\left(\left(\frac{v}{C_w}\right)^{K_w}\right)\right] \tag{13}$$

Step 2: In order to assess the uncertainties of a given problem, the problem must be evaluated several times with different combination of inputs to cover at least the most important or probable conditions. To model the uncertainty associated with the WTG's output power, the desired wind speed samples are generated in each evaluation by an appropriate manner.

Step 3: The generated wind speed samples can be transformed to wind turbine output power using the wind speed-power curve through (15).

$$\begin{aligned} &P_{WTG} = 0 \quad \text{if} \quad v \leqslant v_i \quad \text{or} \quad v \geqslant v_o \\ &P_{WTG} = P_r \frac{v - v_i}{v_r - v_i} \quad \text{if} \quad v_i < v < v_r \\ &P_{WTG} = P_r \quad \text{if} \quad v_r \leqslant v < v_o \end{aligned} \tag{14}$$

Step 4: One of the frequently used approaches to model the wind farms in steady-state power system studies is to assume their generations as negative loads with constant power factors [28]. Hence, the wind farm output powers are modeled here as negative uncertain loads in the corresponding bus (here, it is assumed that the wind farm power factor is kept at 0.85 lag).

Artificial neural network (ANN)

The application of intelligence systems may be an encouraging alternative to remove some drawbacks associated with currently used probabilistic methods.

Introduction to ANN and its architecture

Artificial neural network (ANN) as a computer data processing system simulates the performance of human brain, which is comprised of billions of interconnected cells named neurons [19]. Generally, the ANN architecture can be divided into three parts: input layer, hidden layers, and the output layer. It is claimed that the multi-layer perceptron (MLP) network is capable to numerically approximate any continuous function to the desired accuracy [29]. The architecture of the suggested ANN has MLP structure with Levenberg–Marquardt (LM) learning algorithm. LM training algorithm is one of the most efficient learning mechanisms for the prediction purpose [30]. The LM method trains an ANN 10–100 times faster than the gradient descent back propagation (GDBP) algorithm [31]. Mathematical details of the LM algorithm are presented in [21]. In [32], Kolmogorov's theorem proves that a problem can be solved with MLP having one hidden layer. So, in this work, an ANN architecture based on MLP with a hidden layer is used.

Differential evolution optimization technique

Differential evaluation (DE) is a heuristic population-based search algorithm for optimization problems [33]. The initial population of DE is randomly generated in the solution space, and then evaluated. Afterwards, three parents are chosen and they generate a single offspring which creates next generation candidate. Each candidate of generation is called individual. DE generates a single offspring (instead of two as the genetic algorithm) by adding the weighted difference vector between two parents to a third parent. Formally, the evolution of the proposed DE from a generation to the next generation is based on the following relation:

$$X_{i,g+1} = X_{best,g} + R \times (X_{r1,g} + X_{r2,g}), \quad i = 1 : NG \tag{15}$$

where R is the control parameter proposed by Storn and Price which controls the amplification of the differential variation [33]. In order to widely search the solution space in various directions, control parameter is selected randomly on the range of $[0,1]$.

Combination of the ANN and DE

In order to improve the learning procedure of the ANN in extracting input/output mapping function, ANN is combined with a stochastic search technique (i.e. DE). Although LM is computationally efficient learning algorithm, it searches the solution space in a specific direction (such as steepest descent) and thus, this learning algorithm may be trapped in a local minimum [34]. When ANN is trapped in local minimum during training phase, DE is used to solve the problem. Training ANN without LM and just with DE is a time demanded process and has the problem of convergence. Therefore, DE continues the training phase of ANN by modeling this process as an optimization problem. For this purpose, ANN is trained first by the LM learning algorithm. Then, the obtained weights and bias values are transferred to the DE which can widely search the solution space in various directions with its enhanced exploration capability. Consequently, the DE tries to further minimize the validation error of ANN after LM learning algorithm. The objective function of the DE is to minimize the error of the ANN. In order to convey the knowledge of the LM learning algorithm to the DE, one of the individuals is initially set to the obtained weight and bias of the LM, and the other individuals of the initial population are chosen randomly. After the initialization phase, individuals of the DE move and search the solution space iteratively, until the stopping criterion of the DE is met. Here, if the difference between performances of two iterations does not violate predefined threshold in five successive iterations, the search process is terminated. Then, the components of the best individual of the DE (weight and bias vectors) are returned to the ANN, which are considered as the final weights of ANN. At this point, the training process of ANN is completed.

Application of ANN based online P-OPF

Nowadays, online state estimation of power systems is an essential need for both system study and management. The load, as a highly uncertain parameter, changes ceaselessly; moreover, all uncertain parameters have different values in different time periods. This paper proposes a real time probabilistic power system state estimation based on machine learning algorithm. Fig. 1 shows a typical daily mean load curve. As a well-known fact, power system load faces with uncertainty. For the load uncertainty modeling, the frequently used practice is to describe the load uncertainty with a normal distribution function whose parameters are obtained based on the historical data [26]. Here, the loads are modeled through normal distribution functions with mean values equal to the base loads, and standard deviations (STDs) equal to a specific percentage of the mean values [35]. Hereby, it is assumed that the load is normally distributed with mean values the same as depicted in Fig. 1 and the STD equal to a fraction of the mean values during day hours. Generally, an ANN needs a sufficient set of historical data as its training data to map the relationship between input and output variables and then can transform every input variable to the corresponding output variable. If there is sufficient historical data about uncertain variables, the proposed network can

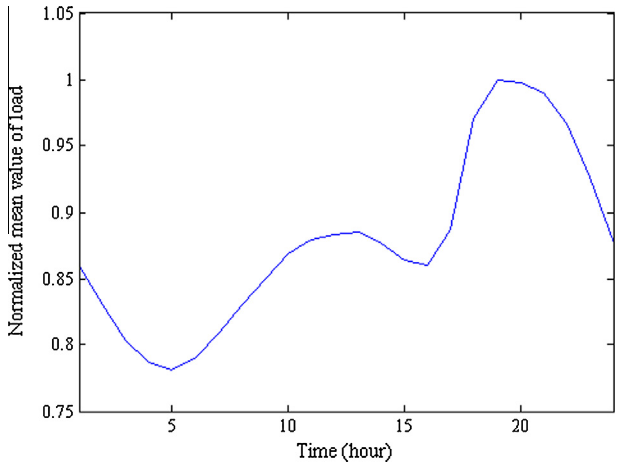

Fig. 1. A typical daily mean load curve.

be trained to be used in real time applications. Otherwise, for each time of day, the train data sets are obtained from probabilistic studies of each time period, in which the mean values of the load are fixed and the STD values of load and the wind speed parameters change in the predefined area. Then, the trained network can obtain true results for any new condition of input parameters in the trained zone. By this way, the training is executed once for a specific period and then, it can be applied during that period as an online system study tool. It must be recognized that the suggested method can be used in other applications such as online probabilistic load flow (PLF) studies, too. The flowchart of proposed method is presented in Fig. 2.

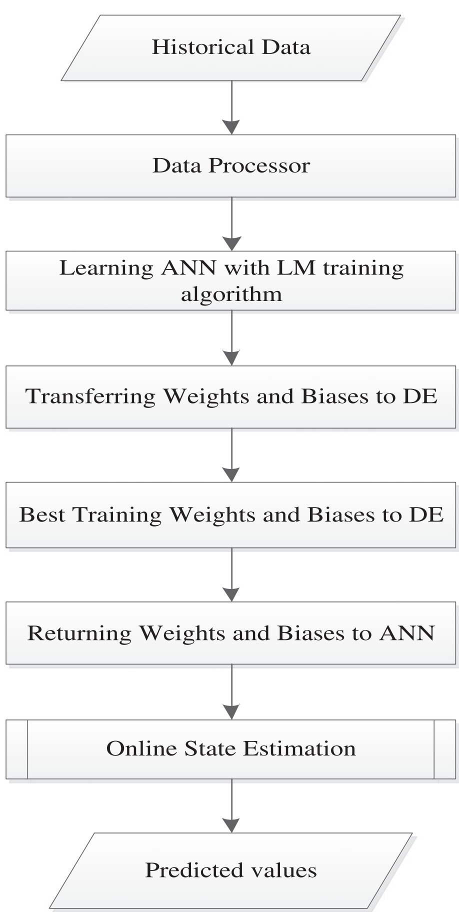

Fig. 2. Flowchart of proposed method.

Case studies and discussion

To justify the effectiveness of the proposed method, two case studies, a 6-bus and a 30-bus test system, are conducted. The proposed method was implemented on a Dell Inspiron 1420 system with a 2-GHz processor and 2-GB of RAM using MATLAB optimization toolbox [36]. All of the codes were written in MATLAB environment.

The wood and woollenberg 6-bus system

This system has 6 buses, 3 generation units and 11 transmission lines with the base power and base voltage equal to 100 MVA and 230 kV, respectively. More technical data about this network can be found in [37].

As noted earlier, the load pattern may change as a result of several reasons such as political issues, industrialization, customer's income, and climate change among the rest. The production of REs such as wind and solar energies may be altered as a direct consequence of climate change. As a simple instance, the wind or solar energy potentials may change because of climate changes in a specific geographic region. In all of these cases, the probabilistic studies must be carried out again which may be a cumbersome procedure and as such inappropriate for an online application. A solution to avoid this requirement is of significant interest. Hence, in this paper, an ANN approach is suggested for this situation.

Assume that this case study has a wind farm installed at bus 4 whose data is given in Table 1. The detailed technical data about used wind turbines is taken from [38] (turbine type: N100 and capacity of 2.5 MW). The maximum load of system is assumed to be 240 MW. As shown in Fig. 1, this system has mean value of load of 210 MW in hour 13.

In the conventional P-OPF study, the goal is to assess the uncertainties associated with output variables with the condition that the value of load STD is fixed at e.g. ±5% of the mean value and the wind speed data is fixed as those given in Table 1. In this paper, the purpose is to go beyond this point. In other words, it aims to interrogate on the uncertainties of output variables as functions of the degree of input variables uncertainty, e.g. the STD of load and the wind speed data parameters. If there are some solutions about the uncertainty of output variables as function of uncertain input variables, an ANN can be trained to obtain the uncertainty of these variables in another new condition. There is an inherent characteristic that the ANN cannot obtain the results out of range that it is trained since the ANN has the capability of accurate interpolation not the extrapolation. As the 6-bus system is a small-scale system, in order to demonstrate the effectiveness of the suggested method, a wide range of variations are chosen and the ANN is trained in that range. To this end, the STD of load is varied between 0% and 25% of the base load, the wind speed weibull shape and scale parameters are changed between the values 8, 0 and 3, 0, respectively.

As previously mentioned, the train data may be obtained from historical data or may be obtained from the simulation of the network with its uncertainty by the probabilistic methods such as MCS, 2PEM, Unscented Transformation (UT) and so forth [9]. At best, all required data to train the ANN are available as historical

Table 1
Wind farm information – case 1.

Parameter	Value
No. of WTGs	8
C_w (m/sec)	8
K_w	3

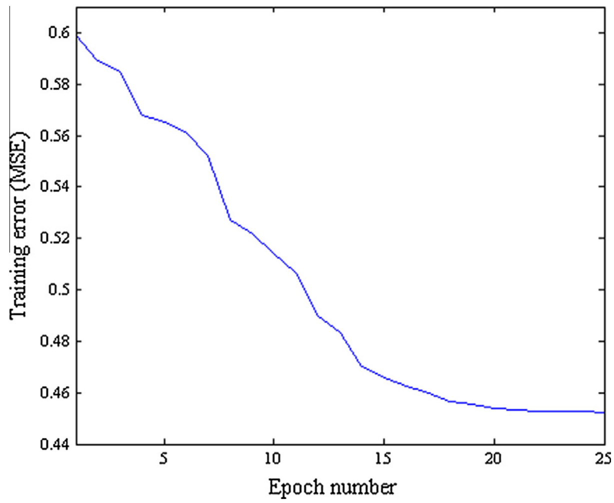

Fig. 3. The trend of error function in each train epoch- case 1 at hour 13.

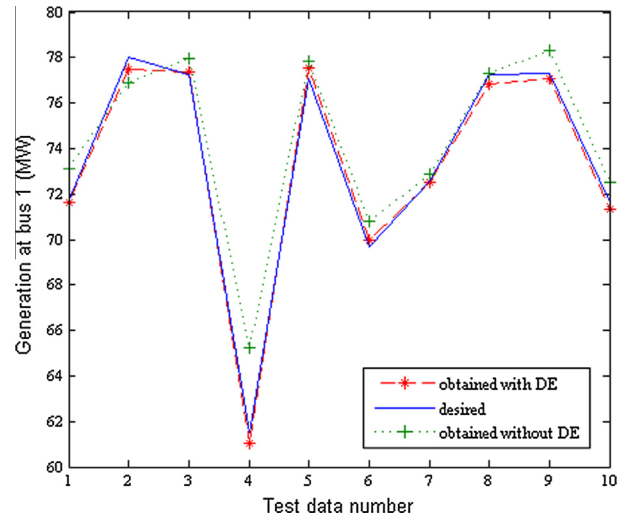

Fig. 4. Predicted and desired values for generation mean value at bus 1- hour 13.

data. At worst, the train data must be obtained by simulation. However, all simulations may be done once and are used forever as historical data. If the area that the network can perform well is to be extended, one can add additional data to the past data set. This means that the train area is extensible. In this paper, about 15% of the train data is considered as test data to evaluate the method performance. Although the method is general and can handle every number of inputs and outputs without any limitation, in this case, the generation at bus 1 and LMP at bus 4 are chosen as the output variables. In this case study, the load STD, wind speed weibull shape and scale parameters are considered as the input variables. Maximum iteration of DE is 100, and stopping criterion of DE is assumed to be 0.001. This means that if the difference between training errors of two iterations is less than 0.001 in five successive iterations, the training procedure is finished. Fig. 3 portrays the trend of error function through the DE. The horizontal and vertical axes of Fig. 3 show training epochs and training error in terms of mean squared error (MSE), respectively. As can be seen from Fig. 3, the DE has reduced training error from 0.6 to 0.45. This confirms that the performance of ANN has been improved about 25% using DE.

Fig. 4 portrays the results of feeding the test data to the trained network to examine the performance of the network. The curves are real values (solid blue[1] line), predicted values without DE (dashed red line), and predicted values using DE (dotted green line) for the generation at bus 1. This figure shows that how the generation at bus 1 varies as function of input variables uncertainties. As can be seen from Fig. 4, it is clear that the proposed method performs well in the P-OPF studies and it can obtain the desired results with a high degree of accuracy. Furthermore, predicted curve accurately follows the desired trend using DE. In Fig. 4, mean absolute percentage error (MAPE) without and with using DE are 1.6% and 0.41%, respectively. In order to compare proposed method with another optimization algorithm, combination of the ANN and PSO has been tested. Prediction error of the generation at bus 1 with PSO is 0.68%.

It must be noted that the LMPs are of the most volatile parameters of the system. So, the results for mean and STD values of LMP at bus 4 in which the wind farm is located are presented in Figs. 5 and 6.

Table 2 compares the run time of the proposed method, the 2PEM, and a 3000 samples MCS approach to obtain the solution

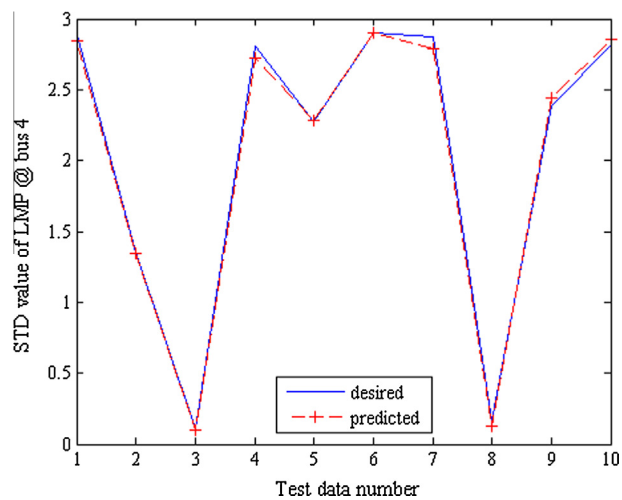

Fig. 5. Predicted and desired curves of STD values for LMP at bus 4- hour 13.

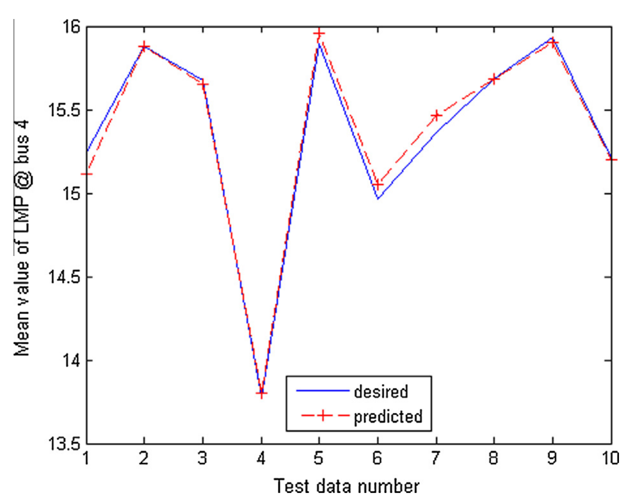

Fig. 6. Predicted and desired curves of mean values for LMP at bus 4- hour 13.

of P-OPF problem for this case study. From Table 2, it can be seen that the proposed method can greatly reduce the computational burden of the problem. The training phase is the most time

[1] For interpretation of color in Fig. 4, the reader is referred to the web version of this article.

Table 2
Run time and accuracy comparison – first case study.

Method	Run time (s)	$MAPE_{Mean}$ (%)	$MAPE_{STD}$ (%)
MCS	1914	0	0
2PEM	5.16	1.6855	3.687
Trained ANN	0.08	0.3564	4.8668

consuming part of the method which is an off-line procedure. Observe that the proposed method has really an interesting performance and can be utilized in real time applications such as LMP forecasting. It takes advantage of historical data or simulations done in the past to face with the new conditions.

The IEEE 30-bus test system

This system has 30 buses, 41 transmission lines and 6 generation units. More technical data about this network can be found in [37]. This system is also assumed to have a wind farm at bus 8 whose technical data is the same as first case study. The system maximum load is assumed to be equal to 189.2 MW in hour 19. For the suggested ANN, the network configuration and DE parameters are the same as before. In this case study, the mean and STD value of LMP at bus 23 and the mean and STD value of losses are considered as output variables.

Figs. 7 and 8 compare the predicted and actual values for the mean and STD value of LMP at bus 23, respectively. The mean and STD value of losses are shown in Figs. 9 and 10, respectively. From the results, it is clear that the proposed method can be used in the P-OPF studies, confidently. Table 3 compares the run time of the proposed method, the 2PEM, and a 3000 samples MCS approach to obtain the solution of P-OPF for this case study. What makes the results particularly interesting is that the run time of the proposed method is not dependent on the number of uncertain variables. Using the trained network for this case study, one can obtain the solution of P-OPF in 0.11 s using the proposed method,

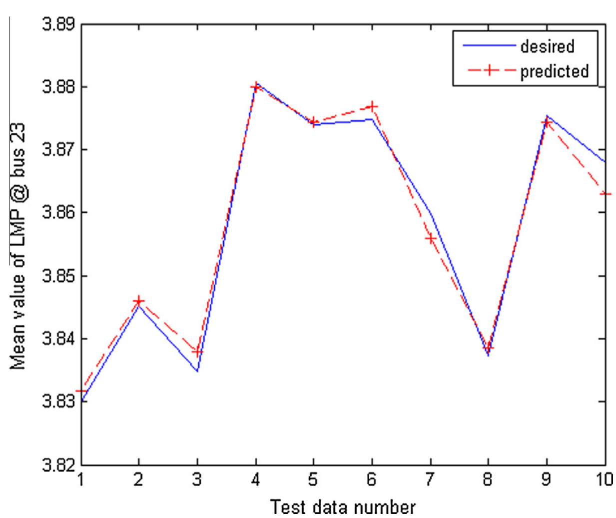

Fig. 7. Predicted and desired curves of mean values of LMP at bus 23- hour 19.

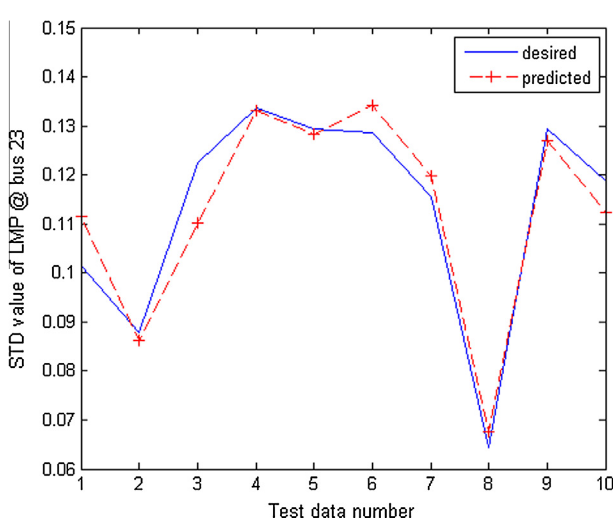

Fig. 8. Predicted and desired curves of STD values of LMP at bus 23- hour 19.

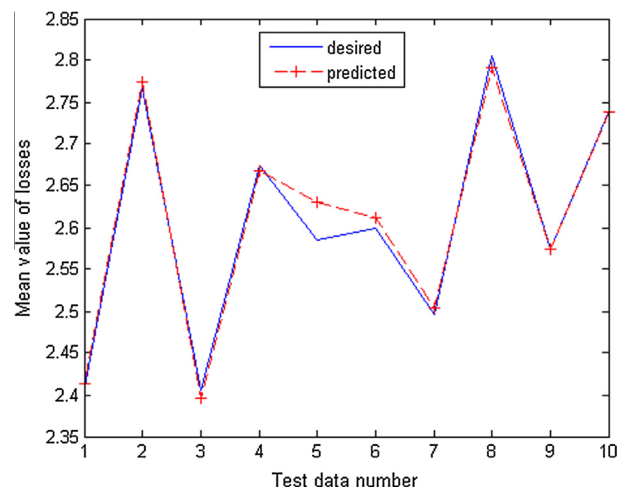

Fig. 9. Predicted and desired curves of mean values for losses- case 2 at hour 19.

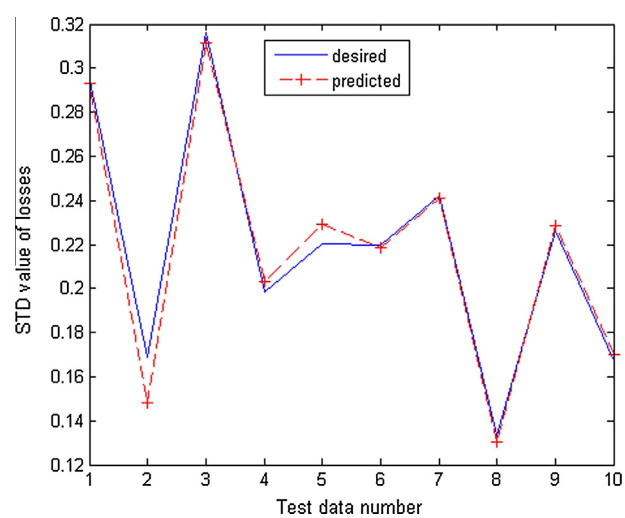

Fig. 10. Predicted and desired curves of STD values for losses- case 2 at hour 19.

Table 3
Run time and accuracy comparison – case 2.

Method	Run time (s)	$MAPE_{Mean}$ (%)	$MAPE_{STD}$ (%)
MCS	21.59e3	0	0
2PEM	367	5.8692	14.2
Trained ANN	0.11	0.2455	3.5006

whereas this time is 21,590 s using the MCS with 3000 samples and 367 s if the 2PEM is used. This supremacy is more sensible as the system dimension enlarges. Along with the number of uncertain variables increases, both the time efficiency and accuracy of 2PEM results decreases more and more [17] but this matter does not hold for the proposed method. On the other hand, the proposed approach actualizes the online power system studies such as online P-OPF.

Conclusion

With legislative and regulatory mandates in modern restructured power systems especially the smart grids, the uncertainty of power grid intensifies more and more. On one hand, the probabilistic studies of system performance are necessary due to different uncertainties imposed to these systems. On the other hand, the online probabilistic studies of the system performance are of huge interest for real time applications such as smart grids operation and control. In this paper, a neural network based approach for real time probabilistic studies such as P-OPF is proposed. One of its applications is the real time pricing of energy in the smart grids. The presented method was examined using two case studies and the obtained results were compared with those of MCS and 2PEM. The proposed method performed well in both case studies from the view point of accuracy and execution time criteria. The proposed method can obtain the results of P-OPF studies in a fraction of a second with a high degree of accuracy while the run times of MCS and even the 2PEM are extremely greater. The generalization ability is the salient supremacy of the method that ennobles it rather than other currently used methods from simulation methods to analytical ones.

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