A New Method Based on Type-2 Fuzzy Neural Network for Accurate Wind Power Forecasting under Uncertain Data

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Abstract

Nowadays, due to some environmental restrictions and decrease of fossil fuel sources, renewable energy sources and specifically wind power plants have a major part of energy generation in the industrial countries. To this end, the accurate forecasting of wind power is considered as an important and influential factor for the management and planning of power systems.

In this paper, a novel intelligent method is proposed to provide an accurate forecast of the medium-term and long-term wind power by using the uncertain data from an online supervisory control and data acquisition (SCADA) system and the numerical weather prediction (NWP). This new method is based on the particle swarm optimization (PSO) algorithm and applied to train the Type-2 fuzzy neural network (T2FNN) which is called T2FNN-PSO. The presented method combines both of fuzzy system's expert knowledge and the neural network's learning capability for accurate forecasting of the wind power. In addition, the T2FNN-PSO can appropriately handle the uncertainties associated with the measured

parameters from SCADA system, the numerical weather prediction and measuring tools.

The proposed method is applied on a case study of a real wind farm. The obtained simulation results validate effectiveness and applicability of the proposed method for a practical solution to an accurate wind power forecasting in a power system control center.

Index Terms

Type-2 fuzzy neural network, PSO algorithm, Medium-term and long-term wind power forecasting, uncertain information.

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1. INTRODUCTION

Nowadays, the utilization of thermal power plants has faced lots of limitations due to some environmental restrictions and deep concerns about the air pollution as well as depletion of fossil fuel resources. That is why in recent years, the development of renewable energy resources particularly wind power plants has played a key role in the electricity energy production in many counties [1]. Wind power plants have many advantages because of their relatively little impact to environment, lack of pollution, and being renewable.

However, one major problem about high penetration of wind power plants into power grids is the uncertainties associated with the forecasting of wind power in different time horizons. Considering high fluctuations of these parameters during different hours, accurate forecasting of wind power is considerably complicated. Based on power system operation requirements, the forecasting can be divided into three time horizons: short-term (few seconds to 30 min), medium-term (30 min to 24 h) and long-term (1 to 7 days). The wind power forecasting in different time periods has an important role in the planning, management and operation of power systems [1].

Recently, a large number of methods have been presented to forecast the wind power. These methods are divided into three parts including physical forecasting methods, statistical forecasting methods and combined forecasting methods. A comprehensive explanation of these methods is provided in [1], where it is mentioned that advantage of each of these presented methods depends on the wind farm conditions. However, among these methods, combined forecasting methods are more useful and also have higher accuracy than others. In [2], the authors present a method for medium-term and long-term output power forecasting of wind turbines as a function of measured parameters by the SCADA system, and the forecasted parameters are obtained from the numerical weather prediction (NWP) (*i.e.* air pressure, humidity, wind speed and direction, and temperature). The recently applied methods for wind power forecasting are summarized in Table 1.

As it can be seen in Table 1, no research has been done for wind power forecast which considers simultaneously uncertainties associated with measured parameters from the SCADA system, the forecasted parameters and measuring tools.

An innovative method based on the artificial intelligence is employed for solving many different problems in power systems instead of performing heavy and time-consuming calculations. These techniques are more practical and suitable for online applications. One of the most popular and practical artificial intelligence techniques is the Type-2 fuzzy neural network (T2FNN) which combines the linguistic interception feature of the Type-2 fuzzy set and the learning capacity of the neural network [31,34-35]. Moreover, this network can handle the uncertainty associated with input parameters.

In this paper, a novel intelligent method based on T2FNN estimation and the particle swarm optimization (PSO) algorithm is proposed for the medium-term and the long-term wind power forecasting under the uncertain data. The presented approach combines the Fuzzy system's export knowledge and neural network's learning capability to forecast the wind power, thus termed T2FNN-PSO. In addition, the T2FNN-PSO can appropriately handle the uncertainties that are associated with input parameters and measuring tools. The performance of proposed method is evaluated by using the obtained data from a real wind farm. This method is implemented for two periods of time (medium-term and long-term). The simulation results demonstrate that the suggested method is accurate and practical for wind power forecasting.

Table 1: Recently applied methods for wind power forecasting.

Reference	Applied method for wind power forecasting
[2]	Combination of imperialistic competitive algorithm and neural network
[3]	Markov-switching autoregressive model
[4]	Adaptive fuzzy logic models
[5]	Takagi–Sugeno
[6]	Fuzzy time series
[7]	Adaptive linear models
[8]	Kalman filter
[9]	Discrete Hilbert transform
[10]	Abductive networks based on group method of data handling (GMDH)
[10]	Adaptive neural fuzzy inference system
[12]	Grey predictor
[13]	Adaptive neural fuzzy system
[14]	Local polynomial regression
[15]	A two-stage hybrid network based on Bayesian clustering by dynamics (BCD)
[16]	Support vector machines (SVM)
[17]	Locally recurrent neural networks (RNN)
[18]	Autoregressive with exogenous input (ARX)
[19]	Autoregressive with exogenous input and multi-timescale parameter (ARXM)
[20]	Random forests
[21]	Neural networks
[22]	Adaptive exponential combination (AEC)
[23]	Multiple architecture system (MAS)
[24]	Least squares-support vector machine (LS-SVM)
[25]	Radial basis function (RBF) neural networks
[26]	The combination of ARIMA–ANN and ARIMA–SVM
[27]	The combination of ARIMA– ANN and ARIMA–Kalman
[28]	The Bayesian model averaging (MBA)
[29]	The combination of soft computing models (SCMs) and similar days (SD)
[30]	The combination of seasonal ARIMA (SARIMA) and least square support vector machine (LSSVM)

In summary, the contributions of this paper can be listed as follows:

1- To present a novel intelligent method based on the T2FNN estimation and PSO algorithm for accurate wind power forecasting.

2- To effectively handle the uncertainty of measured parameters of the SCADA system and the forecasted parameters from NWP and measuring tools by T2FNN.

3- To apply a new training method based on PSO algorithm for tuning parameters of the T2FNN.

The rest of paper is presented as follows:

Section 2 describes the methodology of the T2FNN-PSO for the wind power forecasting. Section 3 introduces the structure and training approach of the proposed T2FNN-PSO. Section 4 explains simulation results and the discussion; and finally, the conclusion is presented in Section 5.

2. METHODOLOGY FOR WIND POWER FORECASTING

Environmental restrictions besides the increase of fossil fuels price have encouraged power system operators to employ renewable energies and specifically wind power during the last decade. On the other hand, an accurate wind power forecasting can play an influential role in both of the operation and planning of power systems. According to [2], the power forecasting of a wind farm can be obtained based on the data obtained from the SCADA system and the NWP (*i.e.* air pressure, humidity, wind speed and direction, temperature). Duo to the chaotic feature of these parameters, the accurate forecasting of generating power of a wind turbine in a practical case is a complex obligation. In addition, this subject becomes more complex when the uncertainties with these parameters are considered in the system model. In our previous work [31], we compared the efficiency and performance of the proposed T2FNN with a multi-layer perceptron (MLP) and radial basis function (RBF) neural networks. The obtained results show a better performance of the proposed T2FNN in terms of accuracy, handling uncertainty and computational costs. Therefore, in this paper, the proposed T2FNN is used to forecast the generated wind power.

In this section, details of our new method based on T2FNN-PSO estimation for forecasting of the generated wind power are designated. The structure of the proposed approach is illustrated in Fig. 1. As it can be seen, each turbine in the wind farm is modeled by using the T2FNN-PSO. The T2FNN-PSO is able to estimate the value of the wind power by using its input parameter. The values of measured parameters by the SCADA system and the NWP are selected as inputs of T2FNN [2]. It’s obvious that due to the natural noise and uncertainties with measured and forecasting tools, the obtained values from the NWP and the SCADA system are associated with uncertainties. Therefore, it is necessary to apply a T2FNN-PSO in order to handle uncertainty of these parameters.

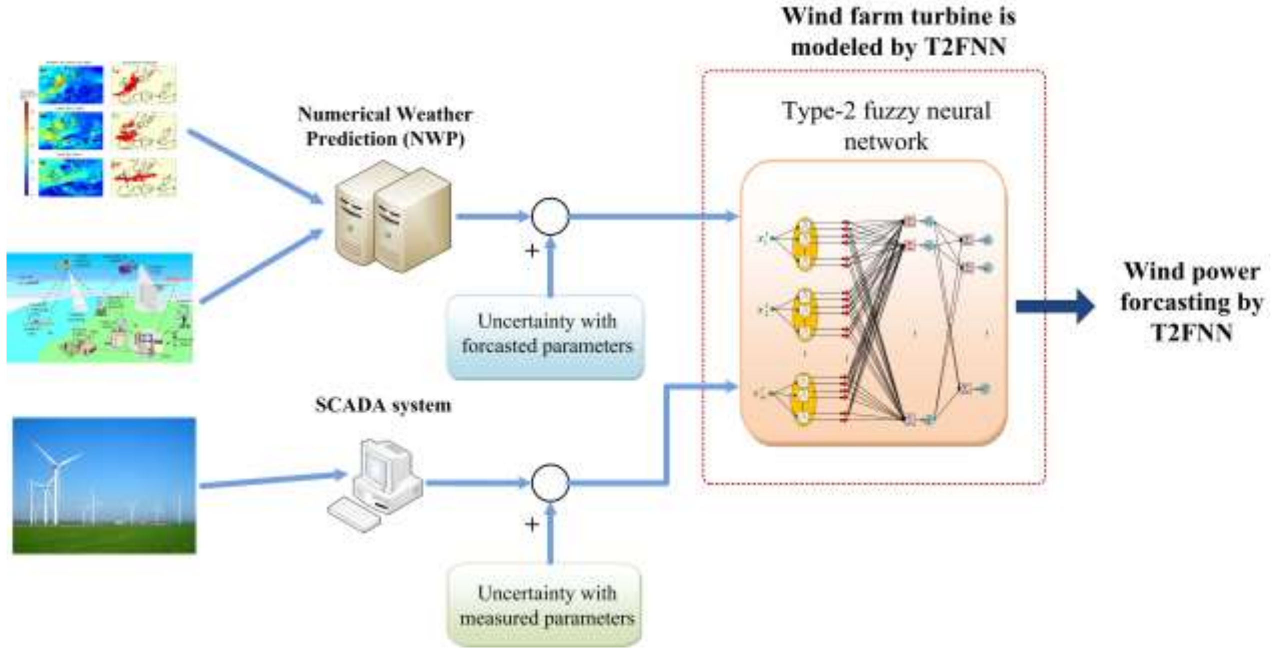


Figure 1: Block Diagram of the proposed method based on T2FNN-PSO.

In order to reach a promising estimate for the value of wind power, it is essential to utilize a correct and accurate training algorithm for tuning T2FNN parameters. In this paper, a new method based on the PSO algorithm is applied to train the T2FNN.

2.1. NUMERICAL WIND PREDICTION MODEL

Nowadays, the weather forecast has a non-negligible impact on the medium-term (i.e. less than 1 hour~24 hours) and long-term (i.e. more than 24 hours) wind power forecasting. NWP focuses on collecting current weather observations and processing these data with supercomputers for forecasting the future status of weather. Therefore, having the accurate status of the current weather is as vital as the numerical models processing the data. Current weather observations serve as input to the numerical models through a process known as data assimilation to produce the outputs of temperature, wind speed, and hundreds of other meteorological elements from the oceans to the top of the atmosphere. The NWP models use physical conversion of energy equations and this allows more realistic downscaling of the data. In fact, high-resolution NWP plays the key role for the wind power forecast [2].

Recently, based on available computational systems, NWP models become more popular in many wind power estimation studies; where several NWP models such as the weather research and forecasting (WRF), conductor-like screening model (COSMO), fifth-generation Penn State/NCAR Mesoscale model (MM5), and RAMS (*i.e.* reliability, availability, maintainability, and safety) are applied [1]. Also, various methods of extrapolation such as the logarithmic law and the wind shear power law have been proposed by other researchers to provide appropriate wind information at the height of wind turbine hub (*i.e.* approximately 50 m) using the meteorological data that are gathered at 10 m above the ground (according to the world meteorological organization (WMO) approval) [32]. Needless to say, the usage of extrapolation laws may create considerable deviations in accurate assessment of the wind power forecasting, specifically for long-term timescales [33].

In this paper, the forecast data obtained from NWP are utilized as a part of input patterns for the proposed model to forecast wind power in medium-term and long-term timescales. In other words, our model is basically a post-processing neural network model for NWP. The reason lies in the fact that the validated data related to the NWP is only available for a certain period of time ahead, and NWP models do not have high accuracy for long period of times. Therefore, it is not possible to solely rely on the NWP model for the long-term forecast of the wind power. To this end, the SCADA and the historical data play a supplementary role for the NWP data. This structure of input data can improve the accuracy of NWP data for the medium-term power forecasting and also compensate the low efficiency of NWP data during the long-term forecasting.

3. PROPOSED TYPE-2 FUZZY NEURAL NETWORK

The neural networks have a desirable performance in terms of recognizing input patterns; however they are weak for explaining how they make their decisions. On the other hand, the Type-2 fuzzy systems can explain the rules of complex systems and imprecise information, and can handle the uncertainties associated with system structure, process and measured variables. However, they are unable to automatically acquire the rules which they apply to make these decisions. Therefore, in this paper, these two intelligent techniques are combined to overcome limitations of individual techniques. The combined system is named the T2FNN system. The T2FNN has been applied successfully in many applications including cognitive simulation, process control, medical diagnosis, financial trading, and engineering design [31]. The structure of a Type-2 fuzzy Gaussian membership function is shown in Fig. 2.

As shown in Fig. 2, the bounded region between lower membership function (LMF) and upper

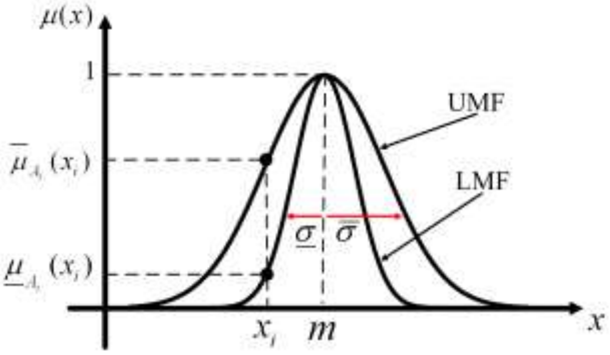


Figure 2: The structure of a Type-2 Gaussian membership function.

membership function (UMF) which is called footprint of uncertainty, can handle the uncertainty associated with the system. $\underline{\mu}_{A_i}(x_i)$ and $\bar{\mu}_{A_i}(x_i)$ are the membership degree of input variable x_i to the UMF and LMF respectively. $\{\bar{\sigma}, \underline{\sigma}\}$ and m are the uncertain standard deviation set and the mean of Type-2 fuzzy Gaussian membership function, respectively. The value of membership degree can be written as follows:

$$\bar{\mu}_A(x) = \exp(-\frac{1}{2}\frac{(x-m)^2}{\bar{\sigma}^2}) \tag{1}$$

$$\underline{\mu}_A(x) = \exp(-\frac{1}{2}\frac{(x-m)^2}{\underline{\sigma}^2}) \tag{2}$$

The structure of the proposed T2FNN is shown in Fig. 3. This network is composed of three layers including input layer, membership layer and inference layer. The operation of each layer of T2FNN is described as follows:

Layer 1-Input layer:

The node output and the node input for every node *i* in this layer can be described as follows:

$$net_i^1(N) = x_i^1, \quad u_i^1 = f_i^1\left(net_i^1(N)\right) = net_i^1(N), \quad i = 1,2,...,m \tag{3}$$

where *N* represents the number of iterations and *m* is the number of inputs. The superscripts of all symbols denote the T2FNN layer number.

Layer 2- membership layer:

In this layer, each node performs a Type-2 fuzzy membership function. Outputs of this layer are fuzzified input nodes which are called linguistic variables. On the other hand, the value of membership

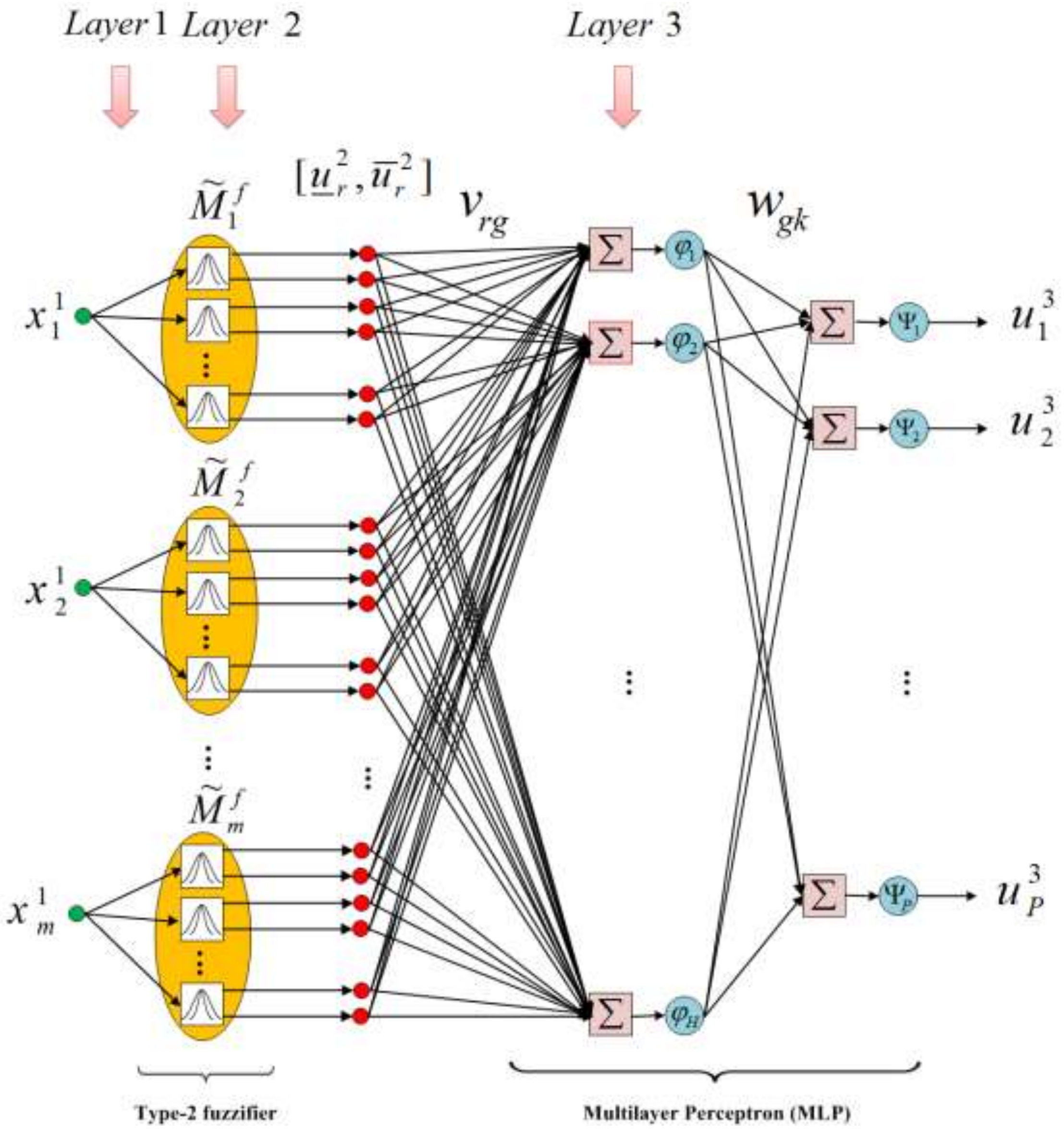


Figure 3: The components of the proposed T2FNN.

degree of each input node to its assigned Type-2 fuzzy membership function is computed. Therefore, it can be derived for the rth node, $r=(i-1)s+j$, as follows:

$$u_r^2=\tilde{M}_i^j\left(x_i^2\right)=f_j^2\left(net_{ij}^2(N)\right)=\exp\left(net_{ij}^2(N)\right)=\begin{cases}\bar{u}_r^2(N) & \text{as} \quad \sigma_{ij}=\bar{\sigma}_{ij}\\ \underline{u}_r^2(N) & \text{as} \quad \sigma_{ij}=\underline{\sigma}_{ij}\end{cases} \quad i=1,\dots,m;\ j=1,\dots,s;\ r=(i-1)s+j$$

$$net_{ij}^2(N)=-\frac{1}{2}\left(\frac{x_i^2-m_{ij}}{\sigma_{ij}}\right)^2 \tag{4}$$

where σ_{ij} and m_{ij} are the standard deviation and the mean of the Gaussian membership function in the jth term of the ith input x_i^2, respectively; and s is the number of linguistic values for each node of input.

Layer 3- inference layer:

This layer is the main part of T2FNN which gives a mapping from input nodes (linguistic variable) to the output (crisp values). The output of *k*th node can be written as follows:

$$u_k^3 = \psi_k\left(w_{0k} + \sum_{g=1}^{H} w_{gk}\varphi_g\left(v_{0g} + \sum_{r=1}^{m\times s} v_{rg}u_r^2 \right)\right), \quad k = 1, \cdots, p \tag{5}$$

where $u_r^2, r = 1,2,\ldots, m\times s$ is the *r*th output node in the layer 2. *H* is the number of neurons in the hidden layer of neural network. The number of neurons in the hidden layer is carefully chosen to provide best results in training phase of the system. Also, φ_g and ψ_k are the activation functions for hidden and output layers respectively. v_{0g} and w_{0k} are the bias on the hidden unit *g* and bias on the output unit *k*. v_{rg} is the weight connecting the input neuron *r* to hidden neuron *g*. w_{gk} is the weight connecting the hidden neuron *g* to output neuron *k*.

The T2FNN requires the adjustment of its parameters in all the layers such that the desired output can be obtained. These parameters consist of $\sigma_{ij} \in \{\overline{\sigma}_{ij}, \underline{\sigma}_{ij}\}$, m_{ij}, v_{rg} and w_{gk} which are adjusted by using the training algorithm. There are several algorithms such as gradient descent, Levenberg Marquardt and resilient back-propagation for training intelligent systems. Selecting an efficient training algorithm is essential for a desirable performance of the T2FNN. In this paper, a new training method is used based on PSO algorithm to obtain a better training of the T2FNN. Details of the proposed method are described in the next sections.

3.1. SETTING OF CONTROLLING PARAMETERS FOR PROPOSED ALGORITHM

As aforementioned, the proposed model is composed of two parts: a Type-2 fuzzifier and a MLP neural network. Controlling parameters should be determined for the proposed model are including the number and the type of the fuzzy membership function for input variables and their corresponding average (*m*) and standard variance (***σ***) values in case of Type-2 fuzzifier; and weights of neurons in case of the MLP neural network.

To this end, the number and the type of the fuzzy membership function (FMF) for input variables are determined based on the knowledge of an expert person. In order to reach optimized values for these parameters, considering the small scale of the search space, the trial and error approach and the extensive search have been employed. Authors have tested different types of membership function (*e.g.* triangular, trapezoidal, piecewise linear, Gaussian, etc.) to reach the best type of FMF. Such the approach has been applied for the number of FMFs. Finally, the value 3 has been determined as the best value for this parameter. It should be mentioned that having more than three membership functions can provide a higher level of accuracy; however, it causes exponential development of the system and subsequently a more complicated network; on the other hand, having values less than three results in loose of accuracy. In fact, a tradeoff has been settled by authors to reach a high quality result with a reasonable computational cost.

In case of neurons weight for the structure of the MLP neural network, average (*m*) and standard variance (***σ***) values for membership functions, the PSO algorithm is utilized to reach optimized values for these parameters. Obviously, classical methods like gradient descent, Levenberg Marquardt and resilient back-propagation could not offer a high quality performance when the number of variables in each pattern of the input data is large (*i.e.* 486 for the presented network).

3.2. APPLICATION OF PSO ALGORITHM FOR TRAINING THE PROPOSED T2FNN

PSO is an optimization algorithm that was first developed in 1995 by Eberhart and Kennedy [36]. The results obtained in [37] shows that the training method based on the PSO algorithm has better performance than other training algorithms because of using less computational time to get higher training accuracy. Therefore, in this paper, the PSO algorithm is applied to train the proposed T2FNN.

According to the previous section, the parameters of proposed T2FNN that should be adjusted by using the PSO algorithm in the training phase include $\sigma_{ij} \in \{\overline{\sigma}_{ij}, \underline{\sigma}_{ij}\}$, m_{ij} , v_{rg} and w_{gk} . The optimization problem proposed in training phase is to search the optimal values of T2FNN parameters by using the PSO algorithm. This results in minimization of the sum of the squared differences between the desired output and actual output. Hence, the objective function can be written as:

$$J(\sigma_{ij}, m_{ij}, v_{rg}, w_{gk}) = \sum_{i=1}^{n} \left(y_d^i - y_e^i\right)^2 \tag{6}$$

where *n* is the total number of training patterns and *i* represents the pattern index. y_d and y_e are the desired output and the actual output, respectively. This objective function needs to be optimized (minimized).

During the training process, in each of iterations, the value of objective function is reduced. This iterative process is ended when a given number of iterations are reached or the value of objective function reaches a predetermined value.

3.3. Training of T2FNN to predict the wind power

In this section, the training process of proposed T2FNN-PSO is explained. In order for the proposed T2FNN-PSO to be applied for estimating the wind power, a correct training procedure of the network is necessary by employing an accurate training data. In this paper, same as [2], the obtained data from Summerside wind farm in Prince Edward, Canada (*i.e.* detailed in Section 3.4) is used for training and testing the proposed T2FNN-PSO [38, 39]. 81 obtained parameters from the NWP and SCADA system are selected as inputs of T2FNN-PSO. These parameters are described as follows:

- 24 parameters for the wind speed forecasting of the next 24 hours.
- 48 parameters for the wind speed of the previous 48 hours.
- 3 parameters for the average forecasted values of humidity, temperature and air pressure of the next 24 hours.
- 6 parameters for the average forecasted values of humidity, temperature and air pressure of the previous 48 hours.

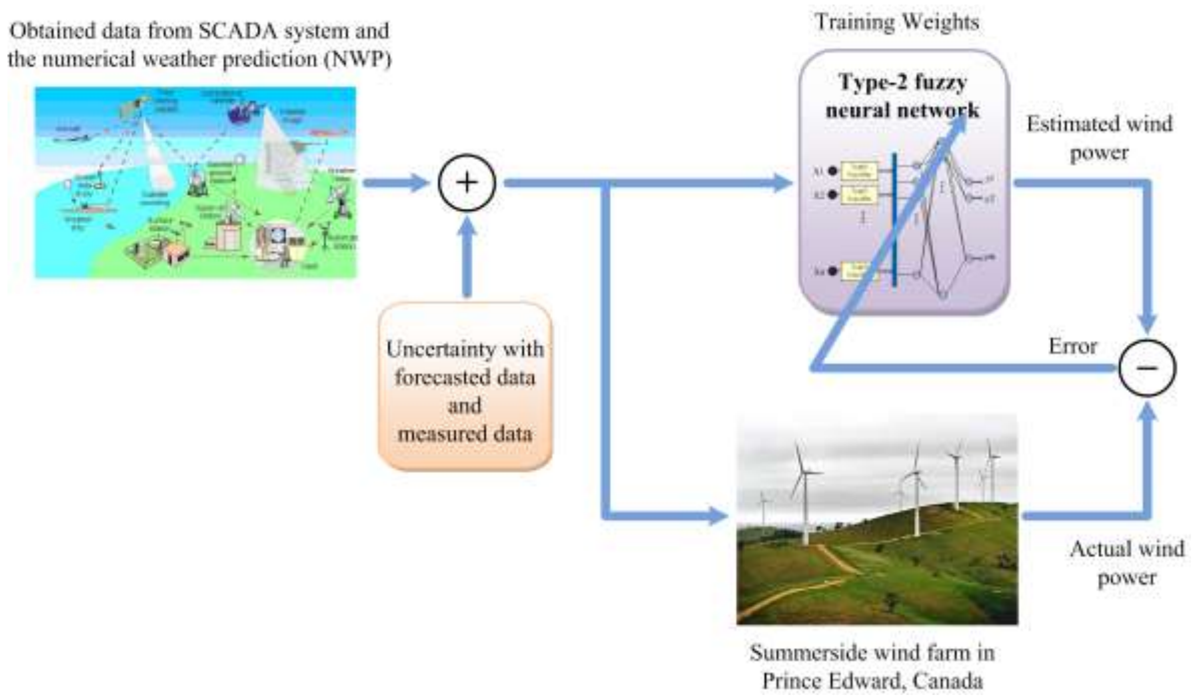


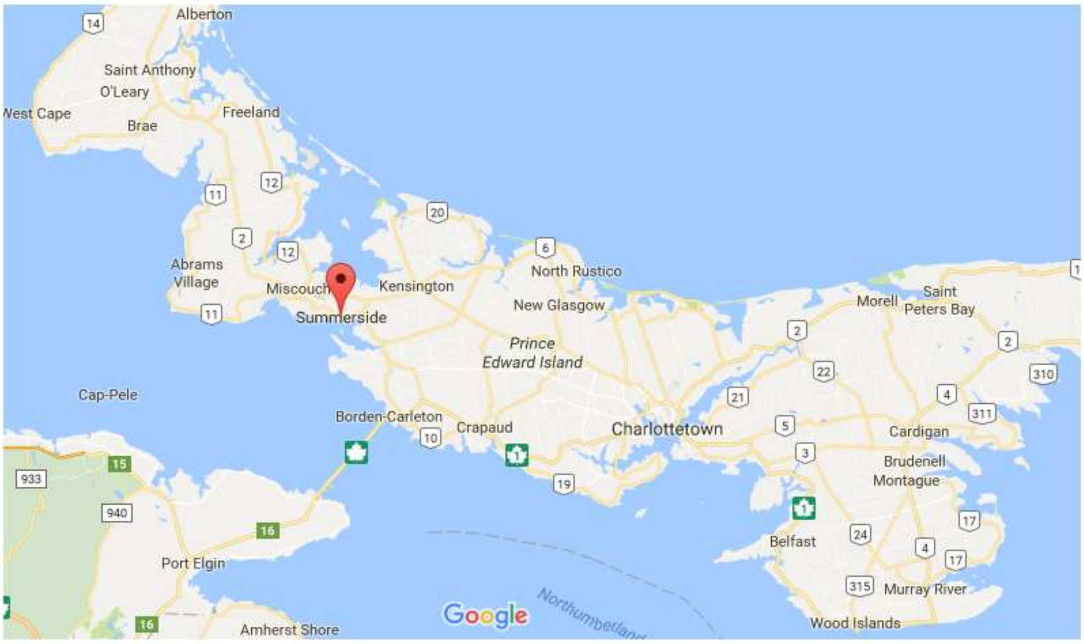
Figure 4: Block diagram of the proposed T2FNN based approach.

The output of T2FNN-PSO is the forecasted value of the wind power for a specified time period. These parameters are used for training and testing the proposed T2FNN-PSO. Fig. 4 illustrates the training diagram of the T2FNN-PSO.

3.4. SUMMERSIDE WIND FARM: LOCATION, SPECIFICATIONS, WIND PATTERN

The Summerside Wind Farm is located in the St. Eleanor neighborhood of Summerside, Prince Edward Island, Canada. Location of wind farm is shown on the map of Canada and Prince Edward Island in Fig .5.

(a) Map of canada



(b) Map of Prince Edward Island

Figure 5: Location of Summerside wind farm on maps of (a) Canada, (b) Prince Edward Island [41].

Isolated ridges and the nearby Atlantic Ocean provide this region with a wealth of wind energy resources. Prince Edward Island has a world-class wind regime, at the northwest tip of the province where wind speeds have been measured for three decades, the average wind speed is 8.0 meters per second at 50 meters height. At the eastern tip of Prince Edward Island, the wind is proved to be almost the strongest. Wind map for the location of wind farm on hub-height of turbine is depicted in Fig. 6. In fact, a glance at the color-coded Wind atlas of Prince Edward Island shows that many areas of the province boast a wind regime that is unparalleled in much of North America.

This wind farm consists of 4 Vestas V90/3000 wind turbines with a combined nominal capacity of 12 MW. The wind farm coordinates are 46°26'15''N & 63°47'59''W. Summerside's $30 million dollar wind farm became operational in December 2009 and has been a valuable asset to the city since then.

Over the course of the year, the temperature typically varies from -11 °C to 23°C and is rarely below -19°C or above 27°C. The warm season lasts for 3.4 months, from June 9 to September 20, with an average

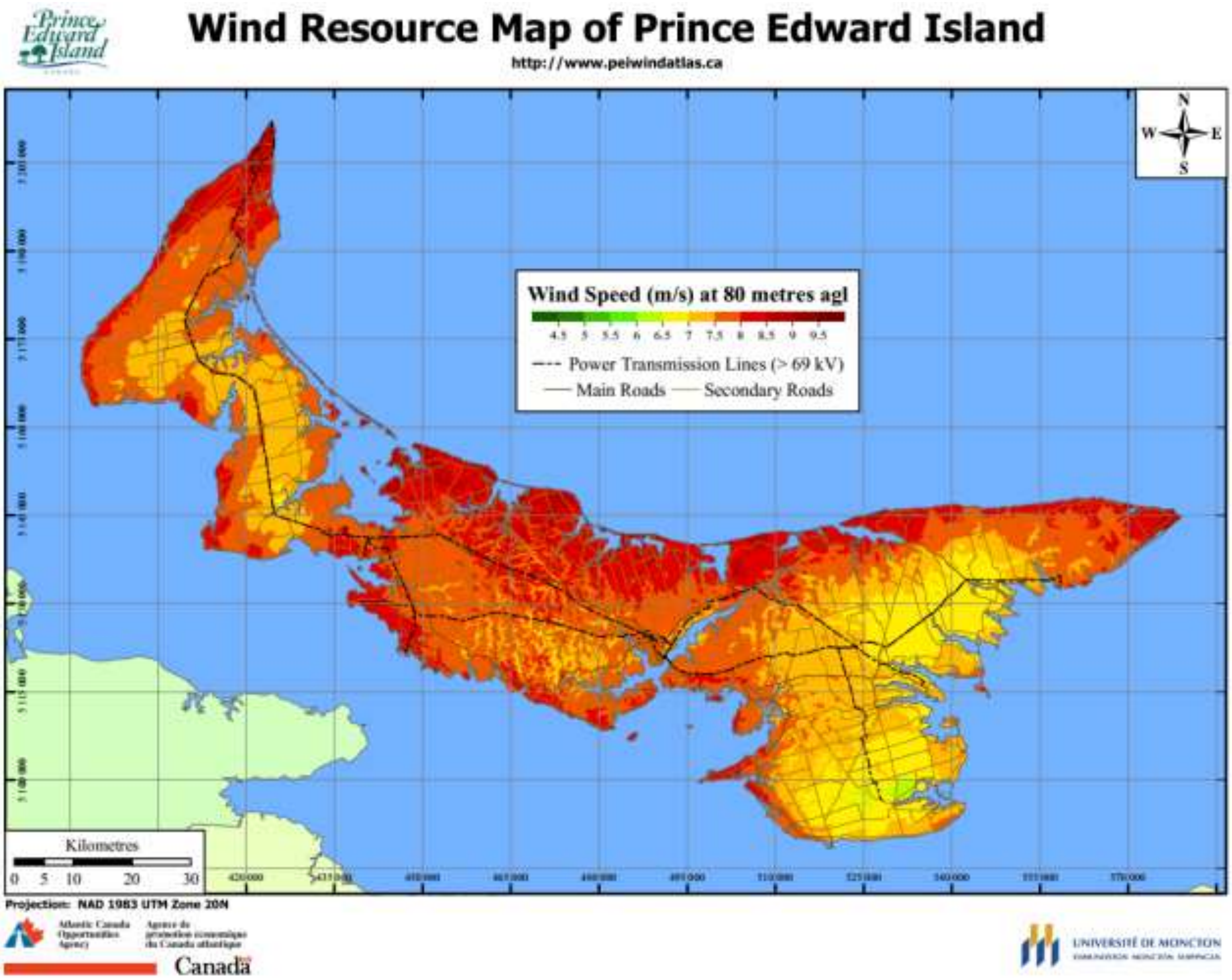


Figure 6: Wind resource map of the Prince Edward Island on hub-height of *Vestas V90/3000* [42]

daily high temperature above 17°C. The hottest day of the year is August 1, with an average high of 23°C and low of 17°C. The cold season lasts for 3.4 months, from December 7 to March 20, with an average daily high temperature below 2°C. The coldest day of the year is January 30, with an average low of -11°C and high of -4°C. Moreover, Fig. 7 shows wind, wave and weather statistics of the wind farm.

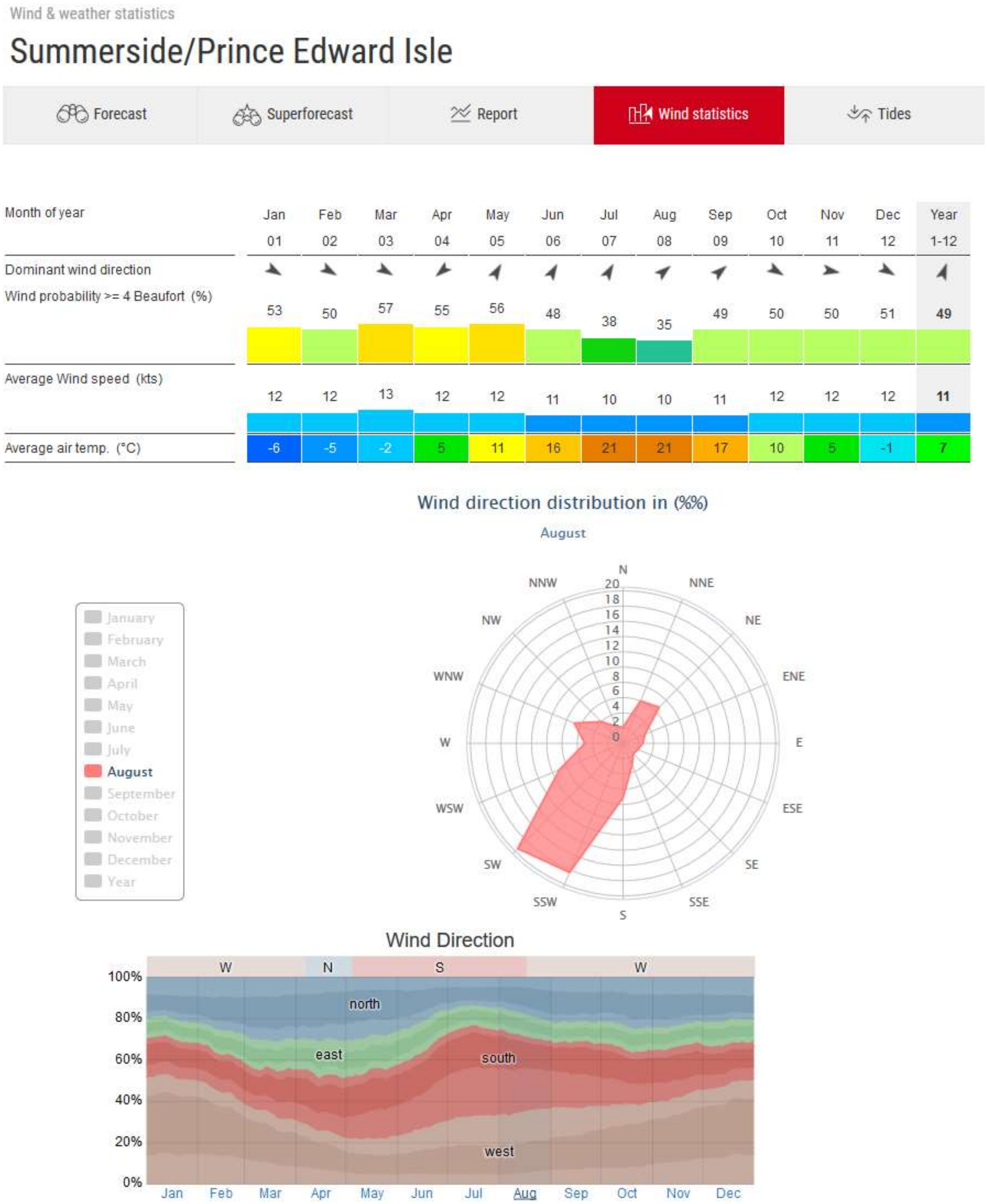


Figure 7: Report from local weather station at East Point/PEI in Prince Edward Island [40]

The predominant average hourly wind direction at Summerside Automatic Weather Reporting System varies throughout the year. The wind is most often from the north for 4.0 weeks, from April 6 to May 4, with a peak percentage of 31% on March 20. The wind is most often from the south for 3.4 months, from May 4 to August 17, with a peak percentage of 44% on July 15. The wind is most often from the west for 7.6 months, from August 17 to April 6, with a peak percentage of 54% on January 11 [42].

It should be stated that Fig. 7 shows the percentage of hours in which the mean wind direction is from each of the four cardinal wind directions (north, east, south, and west), excluding hours in which the mean wind speed is less than 1 mph. The lightly tinted areas at the boundaries are the percentage of hours spent in the implied intermediate directions (northeast, southeast, southwest, and northwest).

4. Results and Discussion

In this section, the proposed approach based on T2FNN-PSO algorithm for wind power forecasting which has been simulated in the MATLAB software is presented. The proposed method has been applied to five different case studies (four case studies for medium-term forecasting and one case study for long-term forecasting). The selected five case studies are detailed in Table 2.

As described in the previous section, there are 81 parameters in the T2FNN-PSO input data that are obtained from the NWP and SCADA system. In this section, firstly, a T2FNN-PSO network should be designed, and then this network is trained by input patterns including 81 parameters.

The design and training approach of the proposed T2FNN-PSO are explained in the following steps:

Step 1: The minimum and maximum variations of 81 input operating parameters are determined.

Step 2: For each of the 81 input parameters, three sets of Type-2 fuzzy are specified as “S”, “M” and “L”. Here, Gaussian membership functions are selected for input parameters as shown in Fig. 8. It should

Table 2. The selected five different case studies for wind power forecasting

Scenario	Forecasting period	Forecasting term
1	3 hours (00.00 AM - 3.00 AM)	medium-term
2	6 hours (00.00 AM - 6.00 AM)	medium-term
3	12 hours (00.00 AM - 12.00 AM)	medium-term
4	24 hours (00.00 AM - 0.00 AM next day)	medium-term
5	36 hours (00.00 AM - 12.00 PM next day)	long-term

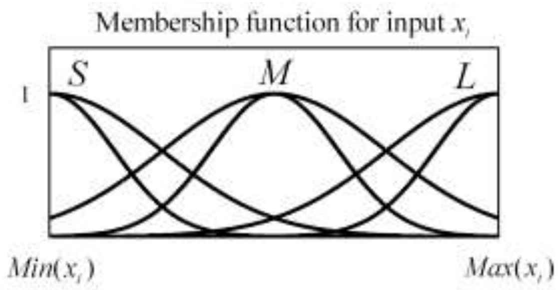


Figure 8: Membership functions of the input parameters.

be noted that, the number of membership functions and UMF and LMF variances are specified using expert knowledge.

Step 3: In this step, after designing the Type-2 fuzzifier, the neural network is designed. Here, a single layer perceptron neural network is applied and trained by using the proposed PSO based training method.

Noteworthy that in case of utilizing a sole neural network, there is no option to consider uncertainties associated with the input data. Moreover, the MLP neural network with several hidden layers should be used because of the non-linear feature of the wind power forecasting problem. Needless to say, a single layer MLP neural network is only capable of offering an acceptable performance for linear problems. However, as one of the novelties of the paper, authors applied a Type-2 fuzzifier to the initial data before entering to the neural network as input patterns. In fact, algorithm makes the initial input data fuzzy and then the fuzzified data are applied to the neural network. This obligation provides several advantages for the proposed method.

First, Type-2 fuzzifier performs as a mapping and therefore it converts the non-linear problem of the wind power forecasting to a completely linear one. Therefore, it is possible to solve the linearized problem using a MLP neural network without adding hidden layers. Second, it is capable of considering uncertainties associated with the input data by employing Type-2 fuzzifier. Third, it greatly reduces the computational cost by applying the proposed method to the given problem because of the high-speed and efficient performance of single layer MLP neural networks without any hidden layers.

The proposed neural network has 486 neurons in its input layer; while number of output neurons is as same as the number of scheduling hours for each case study. In the proposed structure, the outputs of Type-2 fuzzifier are as inputs of the MLP neural network, and there are three Type-2 fuzzy membership functions for each of parameters in the input patterns of the neural network. Considering the fact that Type-

2 fuzzifier has been utilized in this paper, there are two membership values (i.e. upper function and lower function) corresponding to each of these three functions. Therefore, number of the fuzzified input values corresponding to each parameter of input patterns will be 2×3=6.

As it has been mentioned, 81 parameters have been considered as the input variables of the neural network. Accordingly, the number of neurons for the input layer of MLP neural networks can be calculated as 81×6=486. Further details and mathematical expression of the number of neurons for the neural network are provided in [31]. The time series of the wind farm are recorded from August 01 to August 31 for three consecutive years from year 2013 to 2015 with one-hour interval [39, 40]. Therefore, the input data includes 2232 patterns (i.e. for 24 hours × 31 days × 3 years). The forecasting data is given for up to 36 hours ahead at one-hour interval in cases of short-term and long-term forecasting. As mentioned, 75% of the data set has been allocated to the learning procedure and the rest of patterns are used to evaluate the performance of the fuzzy-neural network during the test procedure. Case studies related to 14-15th August, 2015 are shown in this paper to demonstrate the effectiveness of proposed method. Although it is possible to consider the data recorded from one or several complete years as the input, the pattern related to a specific month from several consecutive years has been employed to train fuzzy-neural network. This issue prevents the problem of overtraining during training procedure of fuzzy-neural network due to a large number of input data. However, because the diverse patterns of meteorological data in the location of wind-farm during different seasons or even months, the trained network could not provide acceptable performance with high accuracy.

A linear transfer function is used for the neurons in the output layer. The T2FNN-PSO training is completed around 32s and the final root-mean-square error (RMSE) is completed about 0.015. It should be noted that the simulation is performed on a personal computer with 2.93 GHz Pentium Dual-Core processor and 2GB of random-access memory (RAM), running on MATLAB 7.10 software.

In order to evaluate the efficiency of trained T2FNN-PSO for the different case studies, it has been verified by the testing sets of patterns. Performance of the proposed T2FNN-PSO is evaluated by values of the mean absolute percentage error (MAPE) and the RMSE. These indexes can be computed as follows:

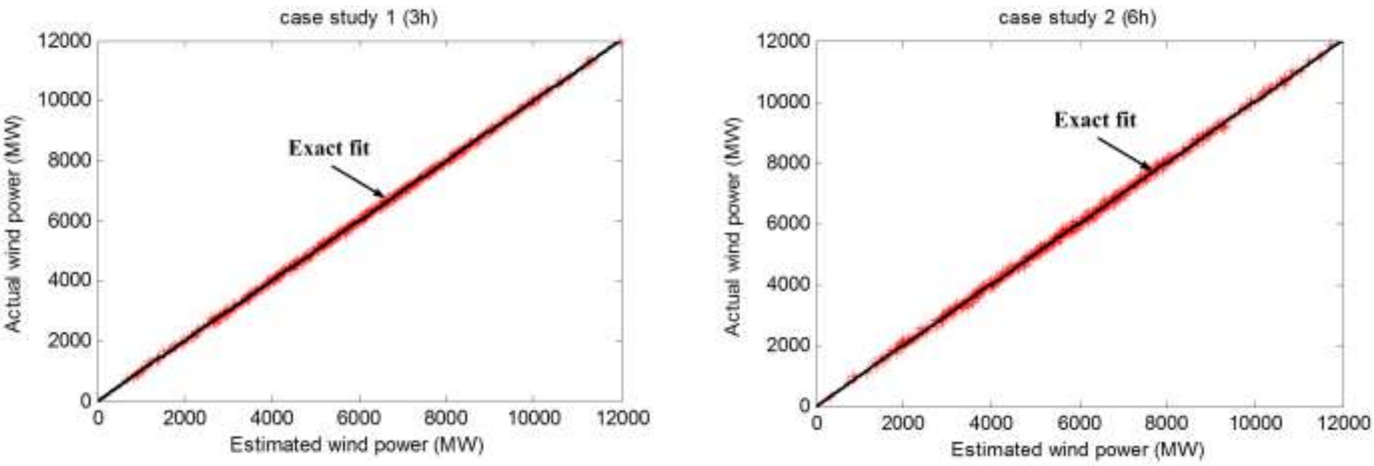
Table 3: The values of the MAPE and the RMSE for five case studies.

Number of case study	Value of RMSE	Value of MAPE
1	3.38 %	0.88 %
2	5.87 %	1.46 %
3	9.14 %	2.34 %
4	12.04 %	2.71 %
5	13.75 %	3.55 %

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{p=1}^{N}(\text{actual Target(p)} - \text{estimated Target(p)})^2} \tag{6}$$

$$\mathrm{MAPE} = 100 \times \frac{1}{N}\sum_{p=1}^{N}\left|\frac{\text{actual Target(p)} - \text{estimated Target(p)}}{\text{actual Target(p)}}\right| \tag{7}$$

where N is the number of testing patterns. Table 3 shows the values of MAPE and RMSE (percentage of full capacity) for five case studies. The obtained results confirm the accuracy of trained T2FNN-PSO for five case studies. The scatter diagram for the wind power for five case studies is illustrated in Fig. 9. Each point in this diagram is shown by (x, y) = (actual wind power, forecasted wind power). As it can be seen, scattering level of the points in the proximity to "Exact fit line" illustrates T2FNN-PSO's accuracy for wind power estimation. Moreover, it can be observed that this accuracy has been maintained acceptable for all the case studies.



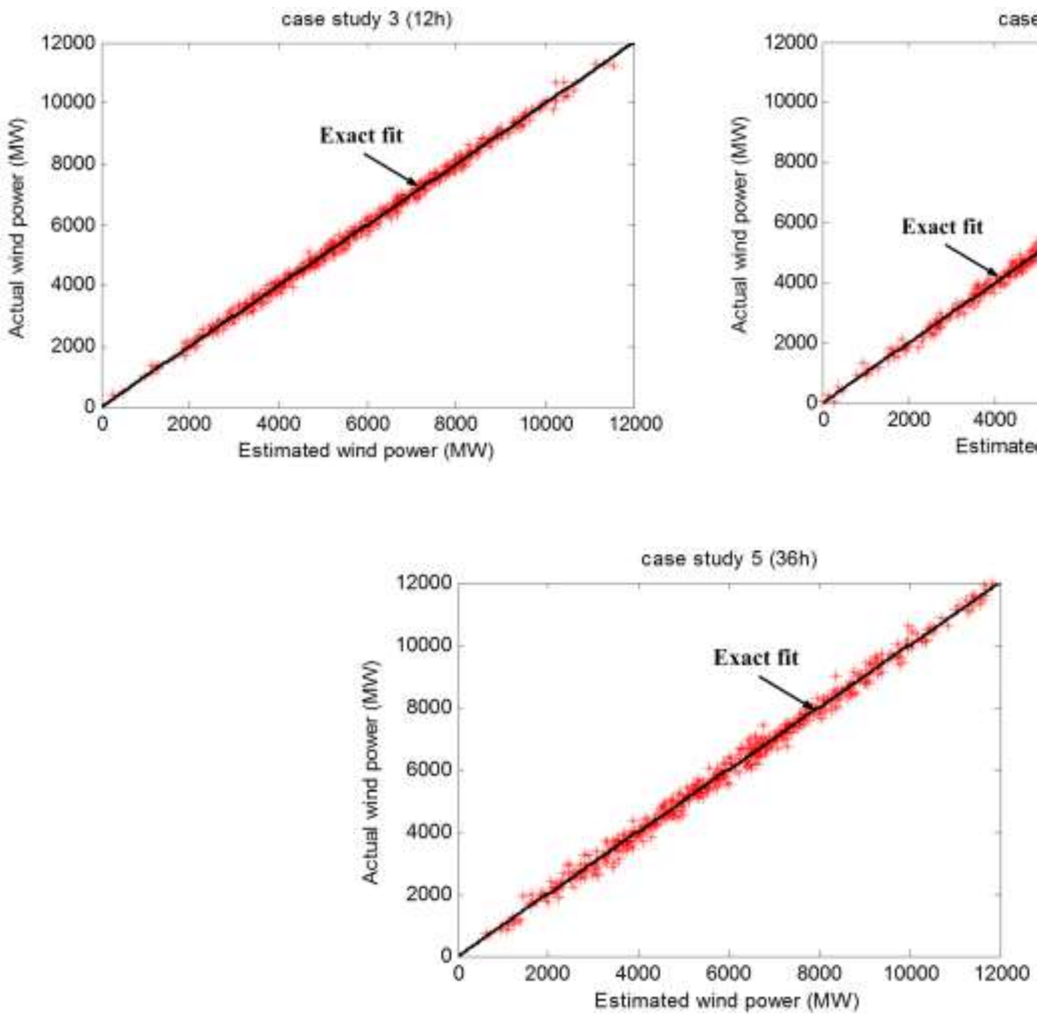
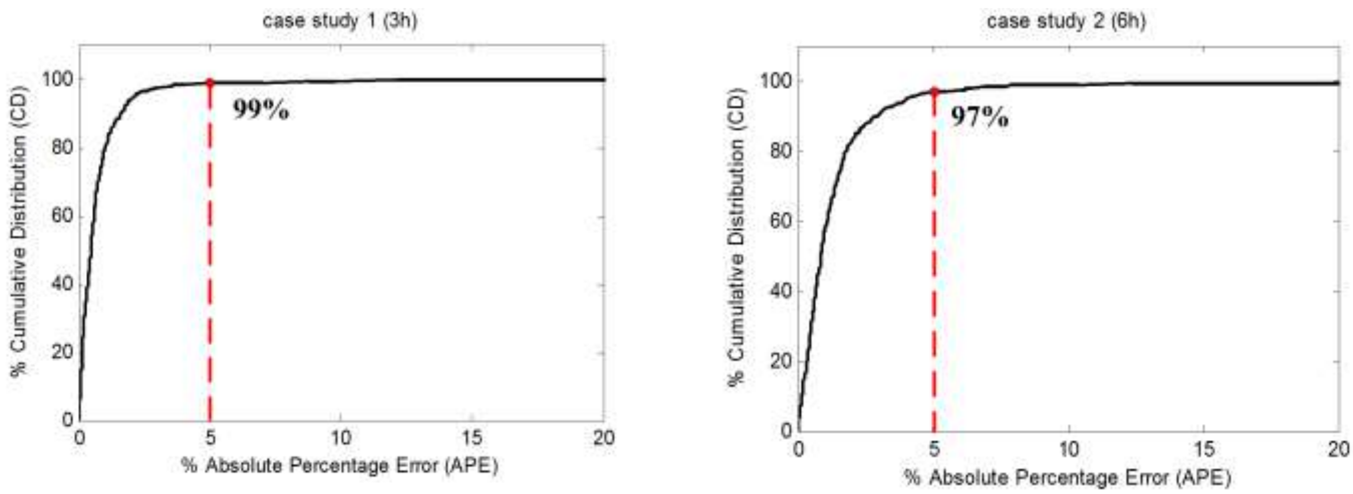


Figure 9: The scatter diagram for five case studies.

The cumulative distribution functions (CDF) of absolute percentage error (APE) for values of wind power predictions are illustrated in Fig. 10.



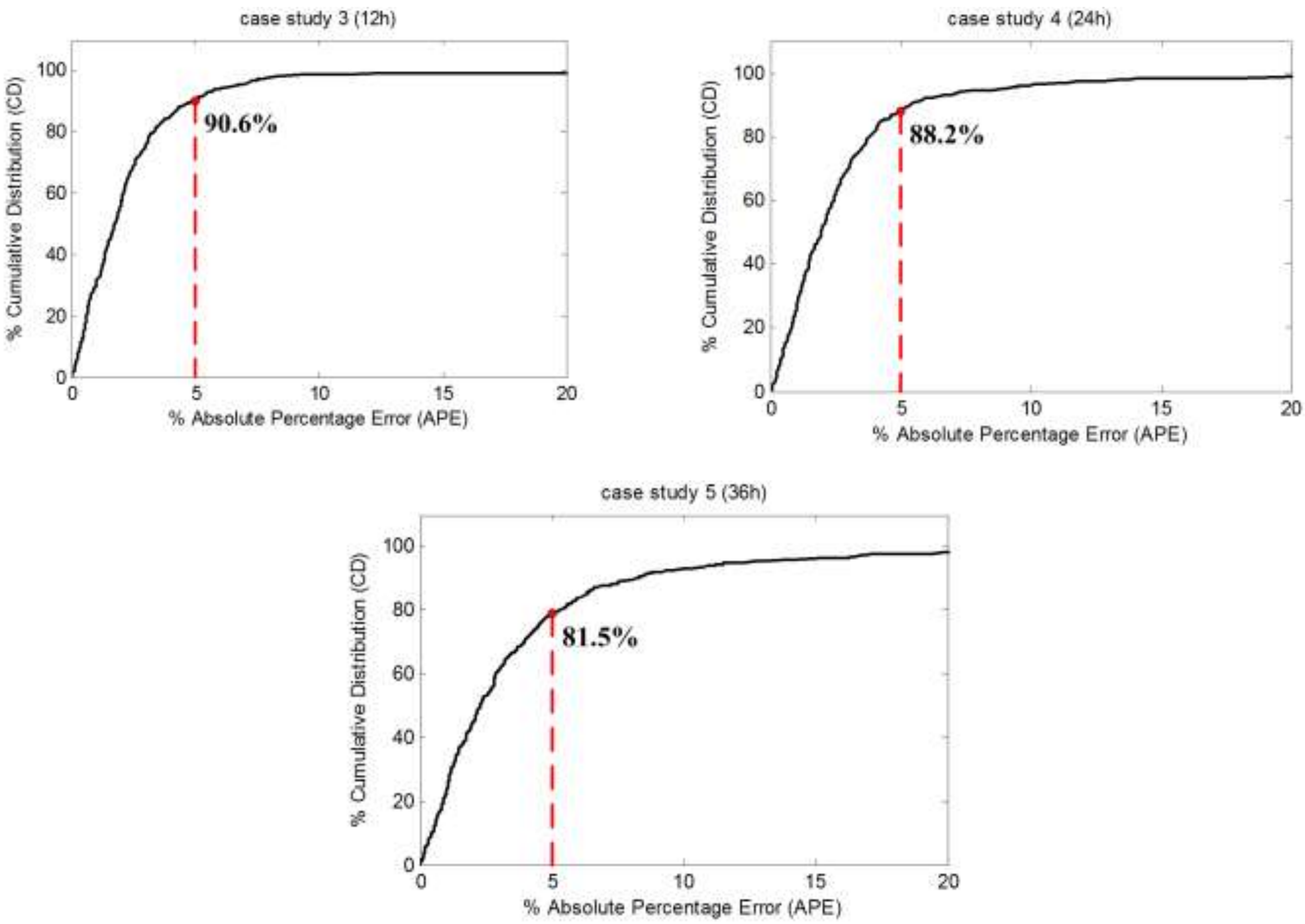
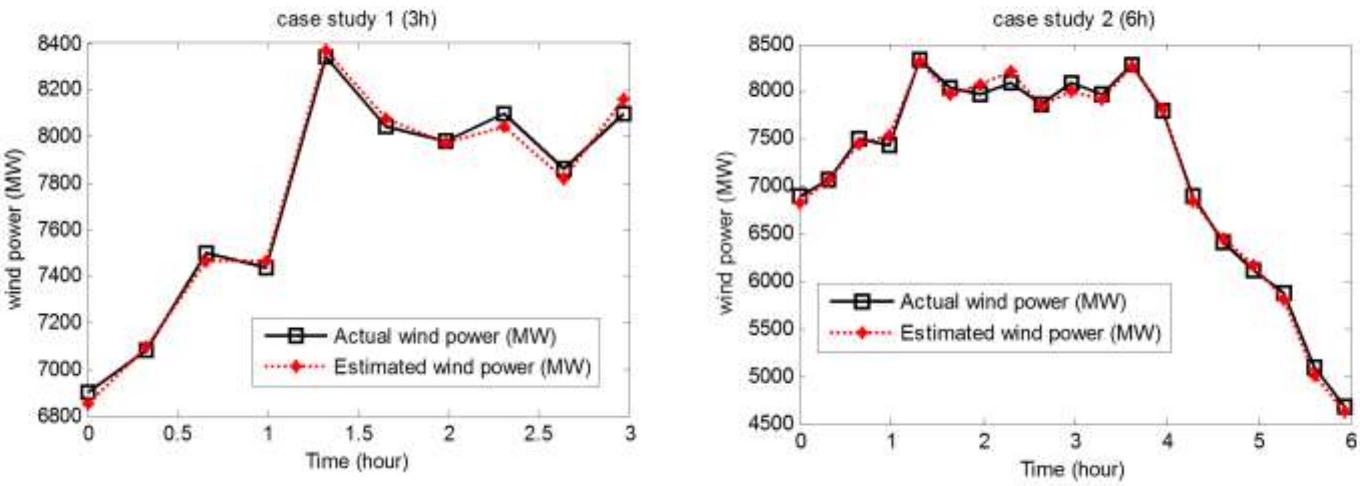


Figure 10: CDF of APE curve for five case studies.

As can be seen in Fig. 10, about 99% of the total test patterns have APE of less than 5% in the case study 1(*i.e.* 3h forecasting). Moreover, in the case study 2, about 97% of the total test patterns have APE of less than 5%. This value for the other case studies is 90.6%, 88.2%, 81.5% of the total test patterns.



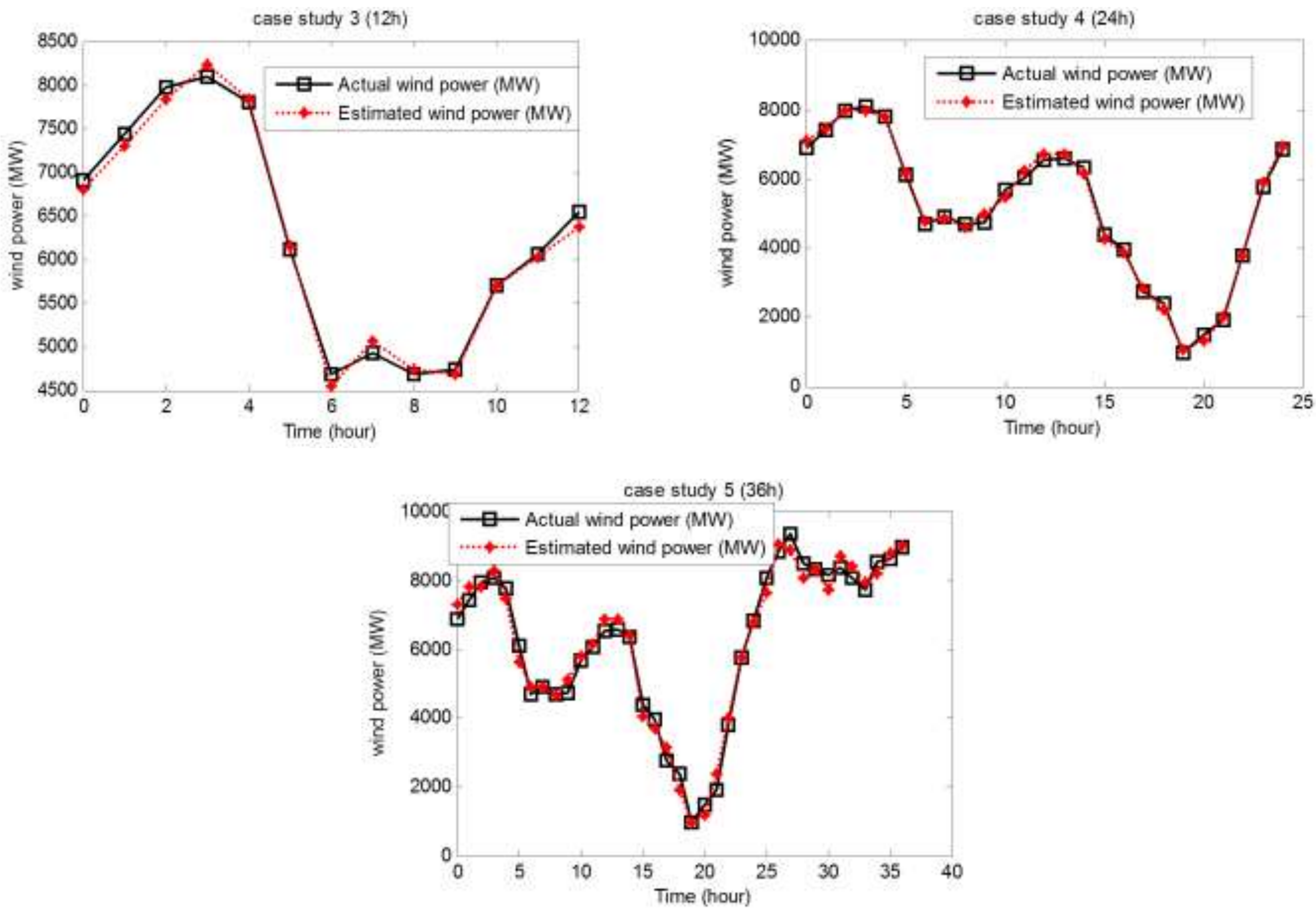


Figure 11: Comparison between the estimated and actual wind power for all case studies.

As shown in Fig. 10, it can be concluded that for all the case studies, small values of APEs (*i.e.* less than 5%) are more frequent (about 85%) than large APEs. The obtained results from simulations show that the proposed T2FNN-PSO gives satisfactory estimation of wind power for all case studies. In order to evaluate the sensitivity of algorithm to input parameters, the estimation of wind power for same scenarios has been done when only the wind speed from the NWP model is used. In fact, nine other input variables of neural network has been omitted. Results for considered scenarios are shown in Table 4.

Table 4: The values of the MAPE and the RMSE for five case studies NWP without auxiliary parameters.

Number of case study	Value of RMSE	Value of MAPE
1	3.43 %	0.89 %
2	6.44 %	1.52 %
3	10.01 %	2.55 %
4	12.62 %	2.92 %
5	14.85 %	3.89 %

Obviously, the quality of obtained solutions are degraded without using auxiliary parameters. In this regard, it should be mentioned that most of wind power prediction approaches use scaling curves to transfer data obtained by NWP (i.e. measured at the height of 10 meters from ground) to the hub axis of wind turbine. Utilizing these curves for wind speed, air pressure, humidity and other factures cause significant error in estimating wind power. However, our approach compensate this deficiency by simultaneous using of NWP data and SCADA system. Moreover, comparing to large number of previous researches in literature which use only wind speed for power prediction, using several meteorological data can provide more accurate predictions.

5. Conclusion

In this paper, a novel intelligent method based on a hybrid T2FNN-PSO algorithm is presented for the medium-term and long-term wind power forecasting under uncertain data. The proposed method can effectively handle the uncertainties associated with the initial data obtained from the SCADA system, NWP and measuring tools by using Type-2 fuzzy sets as Type-2 fuzzifier. The Type-2 fuzzifier layer transforms noisy and uncertain input parameters to reliable linguistic variables. A new training method employing PSO algorithm has been proposed for a fast and accurate offline training of the T2FNN-PSO.

The reliability and performance of the proposed approach have been verified by using the data of a real wind farm. The simulation results show that the proposed T2FNN-PSO method can estimate the wind power for all case studies with a reasonable accuracy. Moreover, the very simple structure of the proposed method leads to reducing the computational time for training phase in online systems. Hence, this method is a practical solution and can be applied for accurate wind power forecasting in power system control centers.

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