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A new strategy for wind speed forecasting using artificial intelligent methods

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A B S T R A C T

A new strategy in wind speed prediction based on fuzzy logic and artificial neural networks was proposed. The new strategy for fuzzy logic not only provides significantly less rule base but also has increased estimated wind speed accuracy when compared to traditional one. Meanwhile, applying the proposed approach to artificial neural network leads to less neuron numbers and less learning time process along with accurate wind speed prediction results. The experimental results demonstrate that the proposed method not only provides less computational time but also a better wind speed prediction performance.

1. Introduction

Electricity generation using wind energy has been well recognized as environmentally friendly, socially beneficial, and economically competitive for many applications. The power-generating efficiency of a wind turbine can be significantly increased if the turbine's operation is controlled based on the information of wind and wind changes at the turbine location. However, due to unpredictable nature of wind speed from time to time and from location to location it is difficult to estimate the utilization factor of wind farms. Therefore, accurate long-term and short-term forecasting of wind speed is vital for wind power generation systems' efficiency [1].

There are various strategies for wind speed prediction that can be classified into two categories: (1) statistical methods that can be subdivided into numerical weather prediction (NWP) and persistence and (2) artificial intelligence techniques that have subdivisions such as neural networks and fuzzy logic.

1.1. *Artificial intelligence methods for wind speed prediction background*

The mathematical description of the wind pattern recognition/prediction problem is to find an estimate $V(k+l)$ of the wind vector $V(k)$ based on the previous m measurements $V(k)$, $V(k-1)$, …, $V(k-m+1)$. In order to have accurate wind speed prediction l is chosen to be very small and this is called short-term wind speed prediction. Application of time-series prediction can be found in the areas of economic, inventory and production control, weather forecasting, and signal processing and control [2]. A general method has been developed to generate fuzzy rules from some numerical input–output data pairs by Wang and co-worker [2,3]. They proposed a five-step procedure for generating fuzzy rules from numerical data pairs and also they showed that how to use these fuzzy rules to obtain a mapping from input space to output space. Meanwhile, they demonstrated that their new method can be used for time-series prediction and compared the results with those obtained using neural network predictor. The developed method in Ref. [2] seems to be simpler and requires much less construction time than a comparable neural network. Lee and Kim [4] also proved that the developed method in Ref. [2] is comparable with neural network and works quite well.

The main drawback of all proposed methods based on fuzzy logic in Refs. [2–4] in wind speed prediction is the large number of fuzzy rule base. For accurate wind speed prediction having high number of wind speed measurements is necessary. However, by increasing the inputs for fuzzy logic block, the number of fuzzy rule base will be increased. Kim and Lee [5] proposed a time-series prediction method using a fuzzy rule-based system. In order to solve the fuzzy logic drawback in non-stationary systems they proposed a method of building fuzzy rules for prediction which utilized the difference of consecutive values in a time series. In Refs. [6,7] a fuzzy model has been suggested for the prediction of wind speed and the produced electrical power at a wind park. They trained their model using a genetic algorithm-based learning scheme at various stations in and around the wind park. They improved the efficiency of short-term forecasting which ranges from a few minutes to several hours ahead. However, because of

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large number of wind speed measurements for fuzzy logic system, the dimension of fuzzy rule base is large and it consumes more computational time.

Artificial neural network (ANN) is a promising technology in wind speed prediction [8]. ANN has been widely utilized in various different fields including transient detection, pattern recognition, approximation, and time-series prediction. Lapedes and Farber [8] proposed an ANN along with feedforward and error back-propagation algorithm in wind speed prediction. Song [9] developed an ANN-based methodology to perform one-step ahead prediction, which is found to be good when the wind data does not oscillate violently. Alexiadis et al. [10] also found that their ANN predictor is about 10% better than persistence model for one-step ahead prediction. In the past many researchers tried to choose the best structure for layer number, neuron number of different layers, and preprocessing and activation functions of ANN in order to get the most accurate forecasting. However, they led to large and complicated networks and long learning time process.

Authors propose a new strategy in wind speed prediction based on fuzzy logic and artificial neural network. The proposed fuzzy logic not only provides significantly less rule base but also increased estimated wind speed accuracy when compared to traditional one. Meanwhile, the proposed ANN has less neuron numbers and less learning time process along with accurate wind speed prediction results. The experimental results demonstrate that the proposed method not only provides less computational time but also a better wind speed prediction performance.

2. Proposed fuzzy logic and artificial neural network structures

The main structure of the proposed method is shown in Fig. 1. From this figure it is clear that instead of direct application of measured wind speeds in time series of $V(k)$, $V(k-1)$, $V(k-2)$, …, $V(k-m+1)$ to fuzzy or ANN predictor and estimation of $V(k+l)$, …, $V(k+2)$, $V(k+1)$, some statistic properties of time-series inputs such as standard deviation, average, and slope have been calculated and have been used as inputs to fuzzy or neural predictor.

First-order linear regression between the date and time topology is applied to find the slope of corresponding input data. Indeed, authors found that these three statistic characteristics represent a perfect knowledge about all the properties of wind speed time series. By reducing the inputs to fuzzy inference system the fuzzy rule base will be reduced significantly. As one will see all wind speed statistic properties can be summarized in small rule base, without sacrificing the estimated wind speed. Meanwhile, the proposed structure in Fig. 1 for neural network will reduce the ANN size by improving the prediction accuracy and will increase the learning process speed. In fact, the preprocessing block extracts the desired futures from the input data and makes the decision easier for ANN which subsequently causes a reduced ANN size.

In order to investigate the effectiveness of the proposed model, many benchmark tests have been carried out using real wind data measured in Rostamabad in northern Iran for 2002–2005 period. These measured data have been averaged for every 30 min interval. For both fuzzy logic and neural network strategies the measured data for first two weeks of February, May, August, and November have been averaged through 2002–2004. For each month 672 samples are used as train data for that month. Corresponding measurements for 2005 are used as test data. Train data have been used for obtaining fuzzy logic rules and neural network learning process. In order to measure the performance of different methods two statistic properties such as root mean square error (RMSE) and coefficient of determination (COD) will be used.

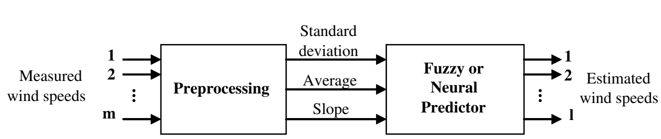

Fig. 1. Proposed wind speed predictor.

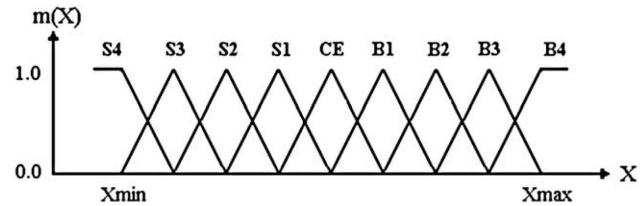

Fig. 2. Fuzzy membership functions.

$$\mathrm{RMSE} = \left[\frac{1}{N}\sum_{i=1}^{N}\left(y_i - y_{\mathrm{ip}}\right)^2\right]^{1/2}$$

$$\mathrm{COD} = 1 - \frac{\sigma_{y,x}^2}{\sigma_y^2}$$

where

$$\sigma_y = \left[\frac{\sum_{i=1}^{N}\left(y_i - y_{\mathrm{m}}\right)^2}{N-1}\right]^{1/2}, \quad \sigma_{y,x} = \left[\frac{\sum_{i=1}^{N}\left(y_i - y_{\mathrm{ip}}\right)^2}{N-2}\right]^{1/2}$$

and N is the total number of data points, y_i are the actual values of y, y_{ip} are the predicted values for y, and y_{m} is the mean of y_i.

Table 1
The statistical analysis parameters for wind speed predictions in proposed and traditional fuzzy methods

m	3	4	5	6	7	8
Traditional						
February 2005						
COD	0.43032	0.43068	0.3996	0.39048	0.3918	0.38088
RMSE	3.3026	3.3615	3.4264	3.5026	3.5562	3.6187
May 2005						
COD	0.9042	0.82836	0.63984	0.4566	0.29352	0.20484
RMSE	1.5566	1.7398	2.1684	2.5494	2.9009	3.2057
August 2005						
COD	0.9591	0.9404	0.9027	0.8721	0.8198	0.7491
RMSE	0.7712	0.9567	1.178	1.3335	1.5747	1.8381
November 2005						
COD	0.8646	0.83412	0.77112	0.66048	0.51744	0.39816
RMSE	1.8117	1.8909	2.0141	2.2054	2.4624	2.7102
Proposed						
February 2005						
COD	0.46788	0.46692	0.47616	0.45768	0.45072	0.42504
RMSE	3.2726	3.275	3.291	3.3061	3.3909	3.3593
May 2005						
COD	0.75612	0.68328	0.71412	0.68916	0.63732	0.57444
RMSE	1.9066	2.1313	2.0645	2.1599	2.3226	3.2046
August 2005						
COD	0.8909	0.8889	0.9072	0.9036	0.8841	0.8896
RMSE	1.2148	1.2258	1.1168	1.1543	1.2623	1.254
November 2005						
COD	0.741	0.7068	0.79704	0.68976	0.6393	0.61104
RMSE	2.021	2.1136	2.0123	2.1398	2.2536	2.642

Table 2
Comparisons for fuzzy rule base

m	3	4	5	6	7	8
Traditional						
August 2005						
Number of generated rules	84	184	313	414	500	590
Full rule base dimension	729	6561	59,049	531,441	4,782,969	43,046,721
Proposed						
August 2005						
Number of generated rules	162	144	132	132	128	120
Full rule base dimension	729	729	729	729	729	729

RMSE is an absolute error between real and predicted values. The less RMSE means the better wind speed estimation. On the other hand, COD allows us to determine how certain one can be in making prediction from a certain model/graph and its values vary between 0 and 1. Zero (0) value of COD means the worst speed prediction and 1 COD indicates the best accuracy in wind speed prediction.

2.1. Proposed fuzzy predictor

In the present study the proposed method in Refs. [2,3] has been applied to produce fuzzy rules from input–output data pairs. As discussed in Refs. [2,3], since each data pair generates a fuzzy rule, there will be some conflicting rules, i.e. rules that have the same IF parts but different THEN parts. To solve this problem, Wang and co-worker [2,3] assigned a degree to each conflicting rules. This degree is defined to be the product of the memberships of its components. The accepted rule is the only one that has the maximum degree. Authors modified the proposed method by Wang and co-worker [2,3] in such a way that from a conflicting group the only rule will accept that has the most occurrence. Only in the case that there are more than one data pair having the maximum occurrence the mentioned degree will be used. Due to disturbance, noise, inexact measurements or records, transient weather conditions such as raining, snowing, icing, temperature variations, etc., some rules may get a big degree whereas their generative data pair will not occur again. Using the systematic method of Refs. [2,3] enables us to

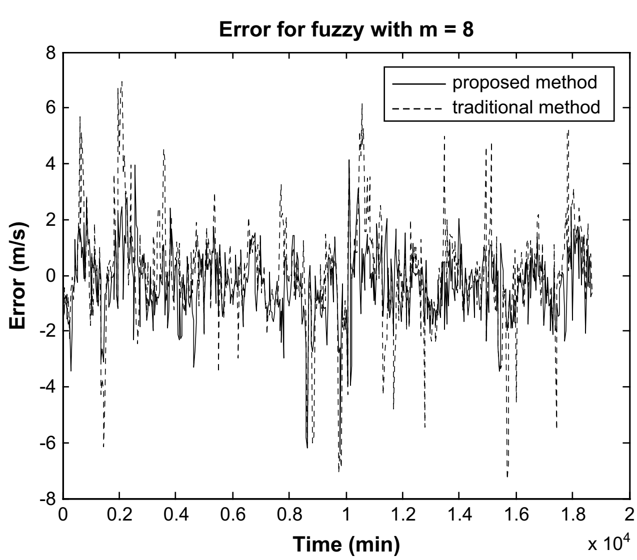

Fig. 3. Wind speed prediction errors for proposed and traditional fuzzy methods.

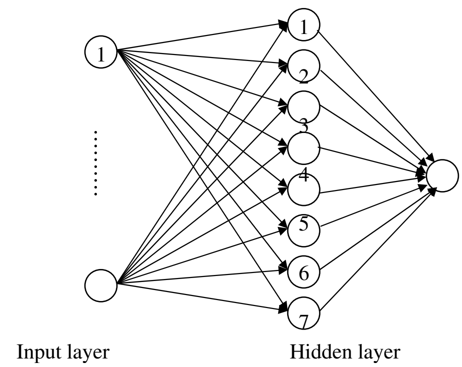

Fig. 4. The proposed ANN structure.

compare results of the proposed and traditional fuzzy predictors. Our modification also improves the fuzzy prediction accuracy. Any shape and number for membership functions (MFs) can be selected. The nine MFs are characterized as 50% overlapping isosceles right triangles for ease of fuzzification as shown in Fig. 2. The more MF numbers mean the more accuracy in wind speed prediction, however, with large rule base dimension.

Table 1 compares the RMSE and COD criteria for proposed and traditional fuzzy methods for $l = 1$ and $m = 3, 4, \ldots, 8$. One can see that for $m > 4$ the proposed method has better accuracy for whole year from February to November. Table 2 indicates the fuzzy rule base numbers for proposed and traditional one. It is clear that the number of generated fuzzy rules as well as the full rule base dimension in traditional method is much larger than the one in proposed strategy. In traditional method the dimension of full rule base increases dramatically as the number of inputs m increases whereas in proposed method, as a result of the limited inputs to the fuzzy block, the dimension remains limited and constant,

Table 3
The statistical analysis parameters for wind speed predictions in proposed and traditional neural methods

m	3	4	5	6	7	8
Traditional						
February 2005						
COD	0.2051	0.1725	0.1806	0.1876	0.2145	0.1944
RMSE	4.5019	4.799	4.9659	4.775	4.5239	4.603
May 2005						
COD	0.3072	0.3082	0.3039	0.3241	0.3181	0.3285
RMSE	3.6149	3.578	3.6531	3.5566	3.4957	3.638
August 2005						
COD	0.5291	0.5201	0.4459	0.444	0.4457	0.4433
RMSE	2.5136	2.5508	2.7904	2.7904	2.7345	2.7706
November 2005						
COD	0.18573	0.15191	0.128	0.13558	0.16502	0.15076
RMSE	3.5109	3.6552	3.7558	3.6791	3.5425	3.695
Proposed						
February 2005						
COD	0.2275	0.2205	0.2217	0.2182	0.2316	0.2945
RMSE	4.4153	4.4893	4.8912	4.2866	4.3563	4.1724
May 2005						
COD	0.3566	0.393	0.4606	0.4806	0.5066	0.5169
RMSE	3.2632	3.2784	3.1719	3.0449	2.6941	2.6849
August 2005						
COD	0.5108	0.5239	0.572	0.5676	0.564	0.5711
RMSE	2.5958	2.5058	2.3477	2.3441	2.3235	2.3227
November 2005						
COD	0.11419	0.19481	0.14467	0.27117	0.27531	0.28232
RMSE	3.7961	3.4877	3.7265	3.2847	3.2292	3.1461

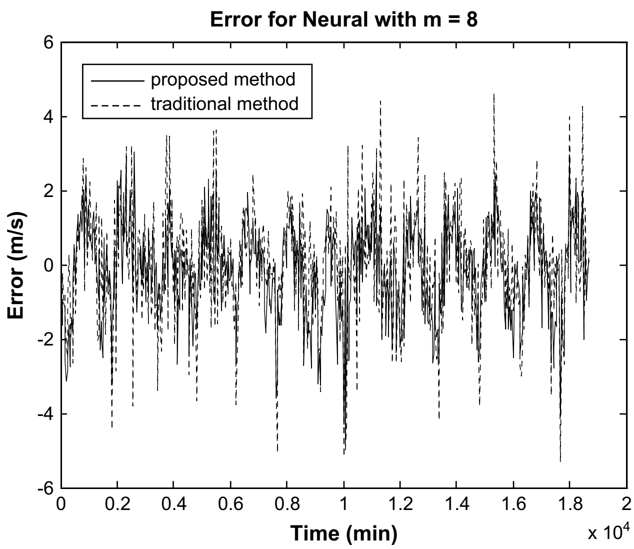

Fig. 5. Wind speed prediction errors for proposed and traditional neural methods.

independent of m. For on-line implementation of wind speed predictor the fast micro-controller such as DSP will be required. By reducing the rule base the computational time of on-line implementation will be reduced without sacrificing the prediction accuracy as shown in Tables 1 and 2. It is believed that the large number for m will increase the prediction accuracy with low number for full rule base but these tables indicate that the big value for m not necessary leads to more prediction accuracy with less full rule base. The wind speed prediction error for proposed and traditional methods in August and with $m = 8$ is shown in Fig. 3. From this figure we can recognize that the error between real and estimated wind speeds is smaller in proposed method.

2.2. Proposed neural network predictor

In this study we applied the method of Ref. [8] for artificial neural network. A feedforward neural network will be used in this research work. ANN is trained by a standard back-propagation algorithm for wind speed prediction. In the training process, we use real wind measurements as input–output pairs. The neural networks are trained with 672 patterns from February to November. The proposed ANN for wind speed prediction which consists of one hidden layer and eight neurons independent of $m = 3, 4, \ldots, 8$ is shown in Fig. 4.

The main purpose of proposed structure is increasing the learning process speed at the same time increasing the accuracy of wind speed prediction. Table 3 indicates a comparison between the accuracy of proposed method with traditional wind speed predictor. One can recognize that the proposed structure for ANN except for $m = 3$ in August and November provides more accuracy for wind speed prediction. In other words new method has less RMSE and more COD. Fig. 5 shows the experimental wind speed prediction error for proposed and traditional neural networks in August and with $m = 8$. From this figure we can recognize that the error between real and estimated wind speeds is smaller in proposed ANN.

3. Conclusion

The new structure for fuzzy logic and neural network in wind speed prediction is proposed. The proposed method provides less fuzzy rule base for fuzzy logic and fast learning process for neural network. The experimental results demonstrate that the new method not only provides less computational time but also has a better wind speed prediction performance.

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