A Novel Fuzzy Predictor for Wind Speed

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***Abstract*— A new strategy in wind speed prediction based on fuzzy logic is proposed. The new strategy not only provides significantly less rule base but also it has increased estimated wind speed accuracy in compare to traditional one. The experimental results demonstrate that the proposed method not only provides less computational time but also a better wind speed prediction performance.**

***Index Terms*— Fuzzy logic, prediction, time series, wind speed.**

I. Introduction

Finding new sources of energy is one of the most important challenges of the current century. Due to increasing demand for renewable energy resources, wind energy and its associated issues have received more attention recently. 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 in to two categories: First group are statistical methods that can be subdivided to Numerical Weather Prediction (NWP) and persistence, and the second group are artificial intelligence techniques that have subdivisions such as neural networks and fuzzy logic.

A. Problem Formulation

The mathematical description of the wind pattern recognition/prediction problem is to find an estimate $V(k+n)$ of the wind speed vector $V(k)$ based on the previous m measurements $V(k)$, $V(k\text{-}1)$, …, $V(k\text{-}m+1)$. In order to have accurate wind speed prediction n 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, signal processing and control [2].

B. Fuzzy Logic Method for Wind Speed Prediction Background

A general method has been developed to generate fuzzy rules from some numerical input- output data pairs by Wang, et. al, [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 [2] seems to be simpler and require much less construction time than a comparable neural network. S. H. Lee et. al [4] also proved that the developed method in [2] is comparable with neural network and works quite well.

The main drawback of all proposed methods based on fuzzy logic in [2, 3, 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 dimension of fuzzy rule base will be increased dramatically. I. Kim et. al, [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 [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 large number of wind speed measurements for fuzzy logic system, the dimension of fuzzy rule base is large and it consumes more computational time.

Authors propose a new strategy in wind speed prediction based on fuzzy logic. The proposed fuzzy logic not only provides significantly less rule base but with increased estimated wind speed accuracy in compare to traditional one. Indeed, as it will be discussed later, the reduced rule base dimension makes it feasible to utilize fuzzy logic in time series prediction problem. The experimental results demonstrate that the proposed method not only provides less computational time but also a better wind speed prediction performance.

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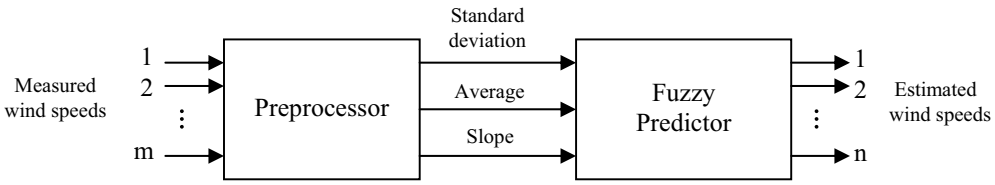

Fig. 1 Proposed wind speed predictor

II. Proposed Predictor Structure

The main structure of proposed method is shown in Fig. 1. From this figure it is clear that instead of direct applying of measured wind speeds in time series of $V(k)$, $V(k\text{-}1)$, $V(k\text{-}2)$, ..., $V(k\text{-}m+1)$ to fuzzy predictor and estimation of $V(k+1)$, $V(k+2)$, …, $V(k+n)$, some statistic properties of time series inputs such as: standard deviation, average, and slope has been calculated and has been used as inputs to fuzzy predictor. First order linear regression between the data and time is applied to find the slope of corresponding input data. In fact, 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 accuracy. Indeed, the preprocessing block extracts the desired futures from the input data and makes the decision easier for predictor which subsequently causes a reduced rule base dimension.

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 to 2005 period. These measured data have been averaged for every 30 minutes interval. The measured data for first two weeks of Feb., May, Aug., and Nov. have been averaged through 2002 to 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. In order to evaluate the performance of different methods two statistic properties such as Root Mean Square Error (RMSE) and Coefficient of Determination (COD) will be used.

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

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

where:

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

and:

N = total number of data points
y_i = actual values of y
y_{ip} = predicted values for y
y_m = the mean of y_i

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 value varies between 0 and 1. 0 value of COD means the worst speed prediction and 1 COD indicates the best accuracy in wind speed prediction.

III. Fuzzy Predictor

In the present study the proposed method in [2, 3] has been applied to produce fuzzy rules from input-output data pairs. As discussed in [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 et. al, [2, 3] assigned a degree to each rule. 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 modifies the proposed method by [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. Because due to disturbance, noise, inexact measurements or records, transient weather conditions such as raining, snowing, icing, temperature variations and etc., some rules may get a big degree whereas their generative data pair will not occur again. Using the systematic method of [2, 3] enables us to compare results of the proposed and traditional fuzzy predictors. Our modification also improves the fuzzy prediction accuracy. Any shape and number for Membership Functions (MF) 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 means the more accuracy in wind speed prediction, however, with large rule base dimension.

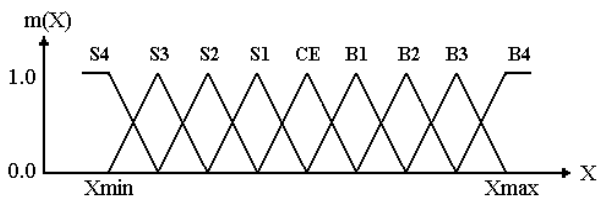

Fig. 2 Fuzzy membership functions

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

			Traditional			
	m:	**3**	**4**	**5**	**6**	**7**	**8**
Feb. 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
Aug. 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
Nov. 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				
	m:	**3**	**4**	**5**	**6**	**7**	**8**
Feb. 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
Aug. 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
Nov. 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 dimension (Aug. 2005)

			Traditional			
m:	**3**	**4**	**5**	**6**	**7**	**8**
Number of generated rules:	84	184	313	414	500	590
Full rule base dimension:	729	6561	59049	531441	4782969	43046721
			Proposed			
m:	**3**	**4**	**5**	**6**	**7**	**8**
Number of generated rules:	162	144	132	132	128	120
Full rule base dimension:	729	729	729	729	729	729

Table 1 compares the RMSE and COD criteria for proposed and traditional fuzzy methods for $n = 1$, and $m = 3, 4, \ldots, 8$. One can see that for $m > 4$ the proposed method has better accuracy for whole year from Feb. to Nov. Table 2 indicates the fuzzy rule base dimensions 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, independent of m. For on-line implement 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. The wind speed prediction error for proposed and traditional methods in Aug. 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.

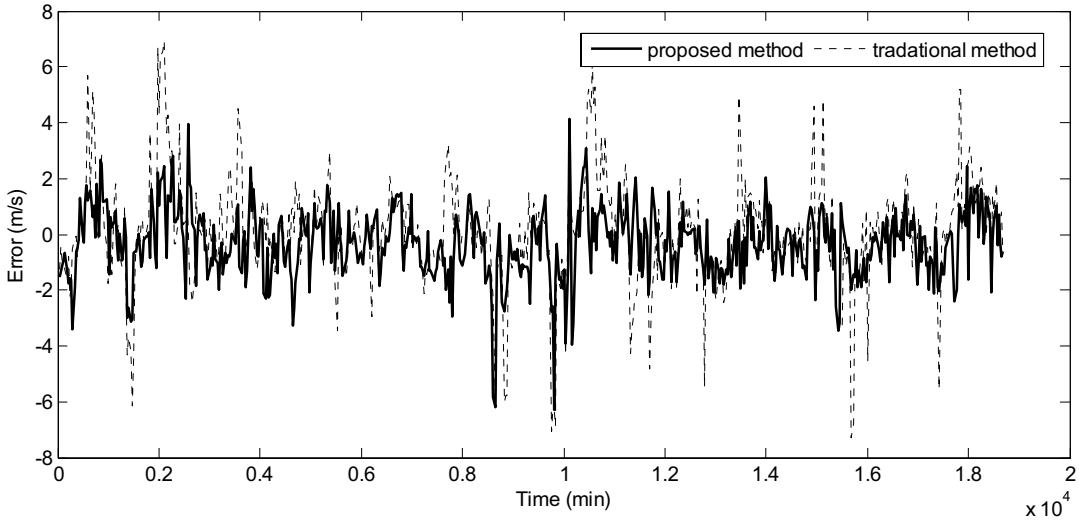

Fig. 3. Wind speed prediction errors for proposed and traditional methods (m = 8)

IV. Conclusion

A new structure for fuzzy logic in wind speed prediction is proposed. The proposed method provides very less fuzzy rule base dimension. The experimental results demonstrate that the new method not only provides less computational time but also it has a better wind speed prediction performance.

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