Wind Speed Modeling and Prediction in Wind Farms Using Fuzzy Logic

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Abstract:

In this paper, the upcoming wind speed is forecasted using the stochastic characteristics of wind speed of previous years. The wind speed is estimated in the fuzzy inference system and simulated with the fuzzy logic. The simulation results illustrate the performance and efficiency of the employed method in predicting the wind speed with high accuracy.

Keyword: Wind Farm, Prediction, Fuzzy

1. Introduction

The needs for energy, shortages of fossil-fueled energy, the environmental effects and air pollution due to the greenhouse gas emission, and global warming are all the factors that cause the use of renewable energy resources in the world. Some renewable energy resources such as wind and solar systems have the advantages of low operating costs while having much capital costs. These renewable resources will have considerable share in future provision of energy demand in several countries.

It should be noted that the economical concerns of the wind farm construction should be evaluated for employing the wind power for electrical generation. For this purpose, the wind power that can be generated in a year for a special region should be estimated using the modeling and prediction of wind speed in that region.

The application of auto-regressive and moving average (ARMA) time series for wind speed forecasting in the wind farm is one of the most conventional method which has been used for data analysis and wind power prediction [1,2].

In some literatures, the role of wind turbines is assessed in both aspects of the sole power plant and in the power network [3]. In this state, the system uncertainties such as wind speed uncertainty, load uncertainty, forced outage rates of wind power units and etc should be defined using the special fuzzy sets. Using the fuzzy relations, appropriate index is obtained for system reliability [4]. The risk evaluation of a wind turbine is introduced in [3] using the wind speed the frequency of occurrence in the system.

In reference [5], the wind power curve is modeling using the adaptive Nero-fuzzy inference system (ANFIS) and this system is also employed for Sogeno fuzzy modeling which has two inputs with four fuzzy rules [6].

In this paper, the wind speed is predicted for the ten-minute time intervals using the 432 input data pairs in ESHTEHARD, a wind farm near the capital of IRAN, Tehran. In the proposed fuzzy inference system, the stochastic characteristics of input time series including the wind speed averages and standard deviations in the previous year are used. This statistic nature illustrates the characteristics and specifications of wind speed time series. In this work, the simulated wind speed is compared with the actual values. Besides, the results are analyzed by changing the membership function and the intervals in which the membership functions are defined. The sensitivity analysis will be also done by variations of fuzzy rules and the consequences will be assessed.

The remaining parts of the paper are organized as follows. In section 2, the proposed method which is containing three modeling stages will be described. The simulations will be carried out on the mentioned case study in section 3. Finally, conclusions will be outlined in section 4.

2. System modeling using fuzzy system

In the proposed system, the inputs are fuzzified firstly and then entered in the framework containing some fuzzy rules based on the If-Then terms. These fuzzy rules make fuzzy outputs of the system which in turn, will be defuzzified. The employed fuzzy modeling in this framework is illustrated in Figure1.

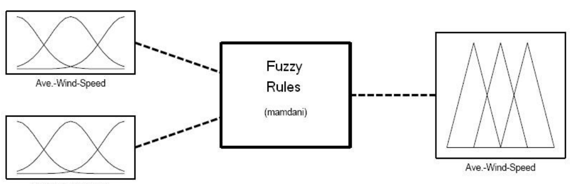

Figure 1. The fuzzy inference system

In this section, three stages for generation of fuzzy rules will be described. It will be shown that the fuzzy rules are used for mapping the input space to fuzzy system. These stages are as follows:

Step 1: Transformation input and output spaces of the given numerical data into fuzzy regions, Step 2: Generate fuzzy rules from the desired input-output data pair, Step 3: Determine a mapping from input space to output space based on the combined fuzzy rule base using the defuzzifying procedure.

2.a) Input and Output Membership Functions

The domain intervals of wind speed are defined. The domain intervals are divided to five regions which are determined by linguistic variables: VL (very low), L (low), M (medium), H (high), and VH (very high), respectively. A fuzzy membership function is assigned to each region.

The membership function of each fuzzy set is assumed to be GBell formation primarily which is illustrated in Figure 2. In the sensitivity analysis of our simulations, the membership function will be changed in order to analyze and compare the related results.

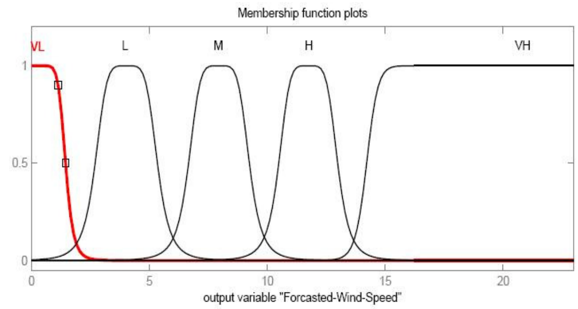

Figure 2. The GBell membership function

2.b) Fuzzy rule generation from the input-output data pair

For generation of fuzzy rules, the wind speed data is used from ESHTEHARD district, for the years 2008 and 2009. The network is trained by wind speed data of 2008 and the wind speed in 2009 is forecasted. The predicted data is compared with the actual values and the fuzzy rules are modified after this comparison. So, the fuzzy system is learned to improve its performance. This procedure is performed for various domain intervals in order to cause the learning effects more accurately. Table 1 shows the obtained fuzzy rules from this procedure.

In the fuzzy rules which are used, the term “AND” logic is employed for the interactions between two inputs. For modeling this expression, different operators are used. The most familiar and simplest operator for this purpose is the minimum operator.

Table 1. Fuzzy rules used in the fuzzy inference system

S. Deviation / Ave. Speed	VL	L	M	H	VH
VL	L	L	L	M	M
L	L	L	M	M	H
M	L	M	M	M	H
H	M	M	H	H	H
VH	M	H	VH	VH	VH

After the definition of the membership functions for fuzzy sets and the specification of the fuzzy rules, the fuzzified outputs can be achieved. After that, the result of each output is associated with maximum operator. In other words, the output is defined using the combination of minimum and maximum operators.

Figure 3 illustrates some of the processes using some above mentioned fuzzy rules.

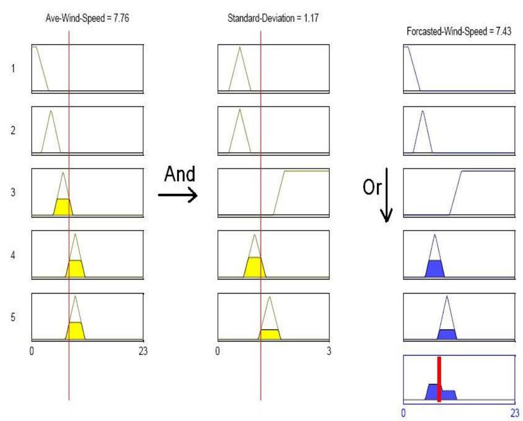

Figure 3. Decision procedure and the rules applied in the fuzzy system

2.c) Mapping determination based on the combined fuzzy rules

The defuzzification strategy is employed in order to define the output control vector using the given inputs. Different methods are used for the data defuzzification such as the centroid method, mean of maximums method, smallest of maximum method, and the largest of maximum method. The defuzzification alternative which is used depends on the nature of the related problem and modeling techniques. In this paper, the centroid method is used for defuzzification purpose. In this method, the defuzzified output is evaluated from the following equation:

$$\hat{x} = \frac{\int \mu_i(x) x dx}{\int \mu_i(x) dx}$$

In which, $\mu_i(x)$ is the membership function of the output fuzzy set and $\hat{x}$ is the output defuzzified value [7].

3. Simulation results

In this section the simulation results of the proposed method for the ten-minute time intervals using the 432 input data pairs in ESHTEHARD wind site are assessed. The input data are gathered in the time span between 2008 and 2008. The wind speed is forecasted for the same time in the future year. For this simulation, the simulated (or predicted) wind speed is compared with the actual values. The sensitivity analyses are performed for various membership functions, various domain intervals, and various fuzzy rules and the obtained results are analyzed.

The simulation result for the GBell membership function is illustrated in Figure 4. As shown in this figure, the simulated wind speeds trace the actual wind speeds with high accuracy which demonstrates a desired prediction. The mismatch value of this simulation with the least mean square error criterion equals 2.076071 which is an accepted error for this calculation.

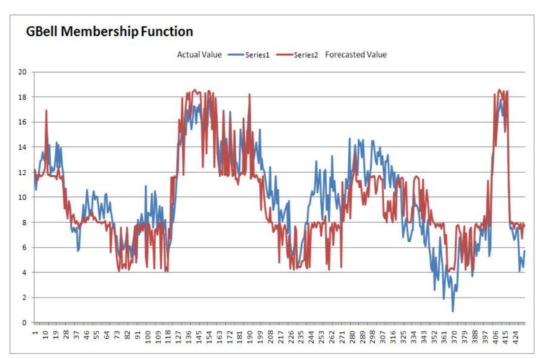

Figure 4. The comparison between the simulated and actual values of wind speed considering the Gbell membership function

Then, the domain interval of the membership function is changed and the simulation is done for the new membership function. The simulation results were similar to the results which were gained for the first case in Figure 4. But, the mismatch value is 2.44174 in this case.

Now, we change the formation of the GBell membership function with the same domain intervals as in the first case. In this case the new function has more width in contrast to the base case. The simulation results show the mismatch value of 2.064571 for this case.

Afterwards, the simulation is performed for the triangular-trapezoidal membership function. The results are shown in Figure 5. The mismatch value for this forecasting using the least square error method is 2.292131.

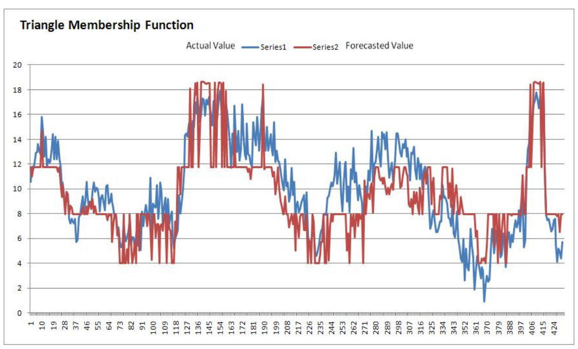

Figure 5. The comparison between the simulated and actual values of wind speed considering the triangular-trapezoidal membership function

For this type of membership function, the domain intervals were changed. For this case, the mismatch error which is calculated based on the least square error criterion equals 2.131057.

The wind speed prediction is performed using the Gaussian membership function. Figure 6 depicts the results of simulated wind speed in comparison with the real data. The mismatch value in this case is 2.042801.

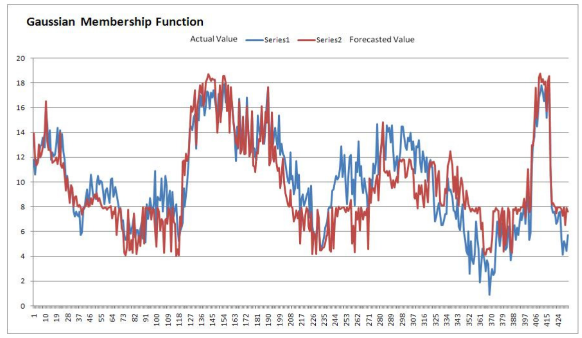

Figure 6. The comparison between the simulated and actual values of wind speed considering the Gaussian membership function

Now, it is investigated that which of the above simulations have more important role in the forecasting approach and should be analyzed more noticeably. For this subject, various forms of membership functions are used and also the domain intervals and the fuzzy rules are changed for evaluation purpose.

Primarily, the formation of membership function has been changed with the assumption of same domain intervals. The results demonstrate that the mismatch differences between the cases were trivial in all these simulation scenarios. The mismatch difference value between the GBell and the Gaussian membership functions was 0.033 while it was 0.22 between the GBell and triangular trapezoidal membership functions. So, the type of membership functions has no significant effects on the wind speed prediction for this case study. The three curves for these membership functions are shown in Figure 7 in which the blue, the red, and the green curves show the predicted wind speed for GBell, triangular-trapezoidal, and Gaussian membership functions, respectively. The difference in simulation is not trivial since the three curves track each others in the most regions.

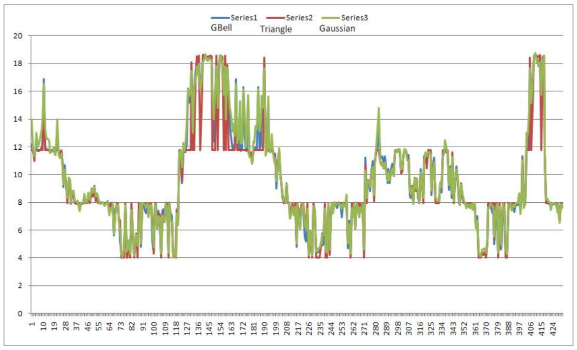

Figure 7. Comparison of wind speed simulation for various membership functions

For the variations of domain intervals, the GBell membership function is assumed. The most variations are applied for the domain intervals. In this case, the mismatch difference values which are achieved are more than the related values in the case of changing the type of membership functions. So, the domain intervals should be selected more accurately in order to minimize the mismatches. Wind speed predictions with different domain intervals are illustrated in Figure 8.

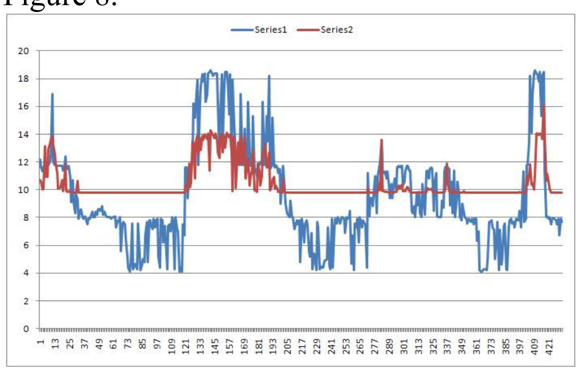

Figure 8. Comparison of wind speed simulation for various domain intervals

Results show the importance of selecting the appropriate domain intervals and considering the deviation of data with high precision.

In the subsequent part, the fuzzy rules are changed. The 10 fuzzy rules among the 25 created fuzzy rules for this problem are shifted to a lower level. This variations change the results considerably as shown in Figure 9 for the simulated and actual wind speeds in these two cases.

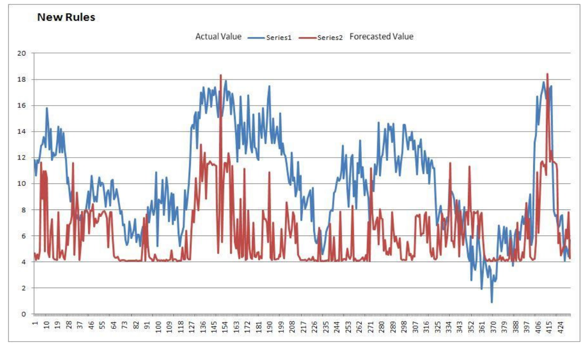

Figure 9. The comparison of simulated and actual wind speeds by changing the fuzzy rules

Therefore, the creation of appropriate fuzzy rules is an important factor for increasing the preciseness of the simulation. The more accurate for the fuzzy rules make the prediction more exactness. So, the above factors should be taken into consideration for improving the accuracy and consistency of forecasting and the setting must be in such a way that the best prediction with the least error will be obtained.

Different criteria have been proposed for evaluation of the performance of the forecasting algorithms. The first criterion is the root mean square error which is defined with the following equation:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(\text{Actual value}_i - \text{Forecasted Value}_i)^2}{n}}$$

The second is the mean square error as mentioned previously and is defined with the following relation:

$$MSE = \frac{\sum_{i=1}^{n}(\text{Actual value}_i - \text{Forecasted Value}_i)^2}{n}$$

And finally, the third is the mean absolute error that can be defined as below:

$$\text{MAE} = \frac{\sum_{i=1}^{n}|(\text{Actual Value}_i - \text{Forcasted Value}_i)|}{n}$$

If the mismatches which are calculated by the above equations become lower, it will be shown that the prediction error is less and the simulated wind speeds are approach to the actual values. The mismatch values which were calculated by various criteria for different cases are presented in Table. 2.

Table. 2. The mismatch values for wind speed prediction by various criteria for different cases of membership functions, domain intervals and fuzzy rules

Cases \ Criteria	RMSE	MSE	MAE
GBell membership function	2.076071	4.310069	1.677546
GBell membership function with variation in placement	2.44174	5.962096	1.98293
GBell membership function with variation in domain interval	3.044877	9.271278	2.54695
GBell membership function with variation in configuration	2.064571	4.262455	1.660178
GBell membership function with variation in fuzzy rules	5.27704	27.84715	4.458129
Triangular-trapezoidal membership function	2.292131	5.253866	1.905804
Triangular-trapezoidal membership function with variation in placement	2.131057	4.541403	1.761343
Gaussian membership function	2.042801	4.173038	1.639033

As refereed previously, the domain intervals and the data deviations of the fuzzy system should be selected accurately and the fuzzy rules must be opted with the preciseness and with the council of expert persons.

4. Conclusion

In this paper, the modeling and forecasting of the wind speed for the future year has been done using the real data. The advantage of the proposed prediction method in contrast to the similar methods is that the prediction is performed with the least required data from the previous times. On the hand, in ARMA method, the detailed stochastic historical data is required for the forecasting purpose. This is an important constraint in the simulation modeling. The applied coefficients in ARMA method depend on the specific region in where the wind speed is forecasted. So, providing a general model for all regions (independent to location) is not possible by means of this method.

In the three-day wind speed prediction which is done for the Eshtehard wind site in Tehran, the roles of some important factors in fuzzy inference system were simulated and analyzed. For this purpose, the type and formations of membership functions, the domain intervals of the fuzzy system, and the fuzzy rules have been changed by doing sensitivity analyses. The results demonstrate that the change of some fuzzy rules to a lower level causes the mismatch values to increase. It is concluded that the fuzzy rules generation is the most significant factor in improving the accuracy of the fuzzy forecasting method. If the fuzzy rules are created more precisely, the prediction will be more accurate.

For reducing the values of error in wind speed prediction, it is proposed to add the inputs of the system. In other words, more factors are considered for wind speed modeling. So, the wind speed modeling will be surely more accurate and the prediction will be done more precisely.

5. References

[1] R. Billiton, and L. Gan, "Wind Power Modeling and Application in Generating Adequacy Assessment", WESCANEX 93.apos; Communication Computers and Power in the Modern Environment. Apos: Conference Proceedings, 1993, Pages 100-106.

[2] R. Karki, P. Hu, and R. Billinton, "Reliability Evaluation of a Wind Power Delivery System Using an Approximate Wind Model", University of Saskatchewan, Canada.

[3] A. V. Machias, and G. D. Skikos, "Fuzzy Risk Index of Wind Sites", IEEE Transactions on Energy Conversation, Vol. 7, No. 4, Dec. 1992.

[4] H. Nachtmann, and J. R. Chimka, "Fuzzy Reliability in Conceptual Design", Annual Reliability & Maintainability Symposium, 2003, Pages 360-364.

[5] M. Mohandes, S. Rehman, and S. M. Rahman "Estimation of wind speed profile using adaptive neuro-fuzzy inference system (ANFIS), Elsevier Ltd, 2011.

[6] F. J. Chang, and Y. T. Chang, "Adaptive neuro-fuzzy inference system for prediction of water level in reservoir", Elsevier Ltd, 2005.

[7] L. X. Wang, and M. Jerry, "Generating Fuzzy Rules By Learning From Examples", IEEE Transactions on Systems, Man, and Cybernetics, Vol. 22, No. 6, Nov. /Dec. 1992.