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Evaluation of Optimal Fuzzy Membership Function for Wind Speed Forecasting

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Abstract

In this paper, a new approach is proposed in order to select an optimal membership function for inputs of wind speed prediction system. Then using a fuzzy method and the stochastic characteristics of wind speed in the previous year, the wind speed modeling is performed and the wind speed for the future year will be predicted. In this proposed method, the average and the standard deviation of inputs data are calculated. The membership function shape and the domain intervals are evaluated using the variance of system. This technique prevents from trial and error method for defining the shape and domain intervals of optimal membership function and helps to achieve the desired prediction in a quick way. The wind speed is estimated in the fuzzy inference system and simulated with the fuzzy logic. The sensitivity analyses are performed by changing the input parameters and membership functions shape and the results are compared. The results demonstrate that this new prediction method is a fast and applicable method compared to the other methods since the calculated error will be more than the error of this method if the shape and domain interval of membership function are changed.

Keywords: wind speed prediction, Fuzzy logic, Wind farms, Mismatch value

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1. Introduction

The needs for energy, shortages of fossil-fuelled 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. Wind power is a renewable energy that will share a considerable part in world's future energy production. This renewable resource will have considerable share in future provision of energy demand in several countries.

It should be noted that the economic 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. Also 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. Therefore, accurate long-term and short-term forecasting of wind speed is vital for wind power generation systems' efficiency [1]

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 [2,3].

In some literatures, the role of wind turbines is assessed in both aspects of the sole power plant and in the power network [4]. 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 [5]. The risk evaluation of a wind turbine is introduced in [4] using the wind speed the frequency of occurrence in the system.

In reference [6], the wind power curve is modelling using the adaptive Nero-fuzzy inference system (ANFIS) and this system is also employed for Sogeno fuzzy modelling which has two inputs with four fuzzy rules [7].

In this paper, a new approach is proposed in order to select the optimal membership function for inputs of wind speed prediction system. The wind speed is predicted for the ten-minute time intervals using the 432 input data pairs in Eshtehard wind farms in 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 analysed by changing the membership function's shape and regions 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 modelling 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 Procedure

In the proposed system, the inputs are fuzzified using their average and standard deviation 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 modelling in this framework is illustrated in Fig.1.

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 of 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.

2.1. Input and Output Membership Functions

The inputs of the fuzzy system are the average and standard deviation of wind speed in the previous years. Firstly, the average and standard deviation of each input is calculated. The domain intervals of the variables are determined using the wind speed profile of the related region in previous year. 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 average value is 8.26 for 432 selected input data of wind speed average. This value is defined for the peak of M-region in related membership function. The other region is adjusted due to this. The expected standard deviation of the related averages is 0.85 which is more probable due to the high variations of wind speed. So, the best shapes that can cover this deviations and lead to an optimal prediction are Gaussian and G-Bell membership functions which have high elasticity due to their shapes and change smoothly.

This method is repeated for standard deviation as an input. For fuzzification of the output space, that is the wind speed average in the future year, it can be said that it is in the form of system input which is the wind speed average in the previous year. So the same membership function is considered for the system output.

The membership function of each fuzzy set is assumed to be GBell formation primarily which is illustrated in Fig.2. In the next sections, in sensitivity analysis of our simulations the membership function is changed to Gaussian and other standard forms in order to analyse and compare the related results.

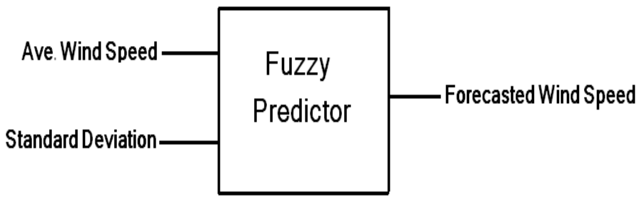

Fig.1. The fuzzy inference system

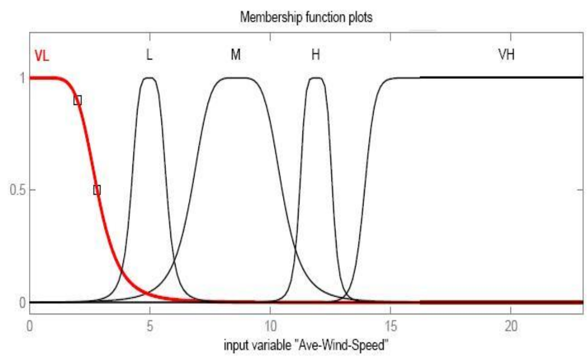

Fig.2. The GBell membership function

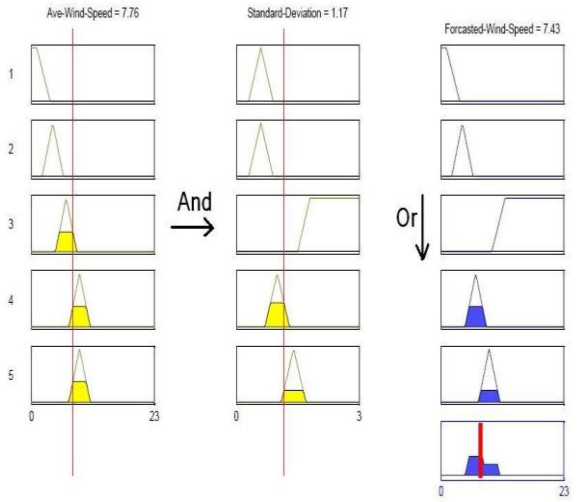

Fig.3. Decision procedure and the rules applied in the fuzzy system

2.2. Fuzzy rule generation from the input-output data pair

For generation of fuzzy rules, the wind speed data is used from Eshtehard district, a place in west of Tehran City for 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.

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

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

2.3. Mapping determination based on the combined fuzzy rules

The defuzzification strategy is employed in order to define the output control vector using the 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 maximums method. The defuzzification alternative which is used depends on the nature of the related problem and modelling techniques. In this paper, the centroid method is used for defuzzification purpose. In this method, the defuzzified output is evaluated from the following equation:

$$\hat{x} = \frac{\int \mu_i (x) x dx}{\int \mu_i (x) dx} \tag{1}$$

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

A 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 2008/7/31 and 2008/8/2. 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 analysed.

The simulation result for the GBell membership function is illustrated in Fig.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 2.033413 which is an accepted error for this calculation.

Now, it is investigated how the changes of domain intervals region in membership function and changes the width of each function impact on the obtained results.

For this purpose, the fixed shape of membership function is assumed and each region of domain interval of membership function is changed and the prediction is performed for new membership function. The simulation results were similar to the results which were gained for the first case in Fig.4. But, the mismatch value is 2.428679 in this case. Now, we change the formation of the GBell membership function with the same domain intervals region. 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.

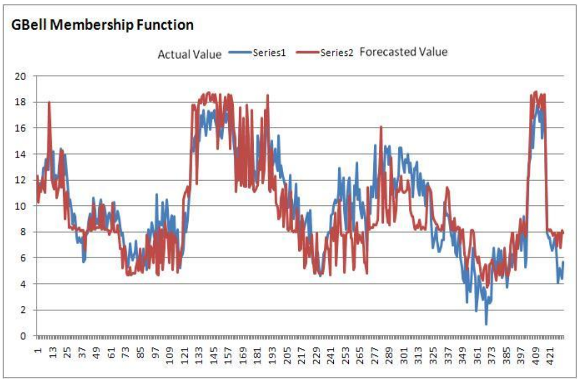

Fig.4. The comparison between the simulated and actual values of wind speed considering the Gbell membership function

Therefore, the width changes of membership function do not impact significantly on results. Change of domain intervals region has more effects than the change of width of membership function and is an important factor in prediction in which the best region (domain) is defined based on the average of input data.

Now, the change of membership function shape is investigated. First the simulation is performed for the triangular-trapezoidal membership function. The results are shown in Fig.5. The mismatch value for this forecasting using the least square error method is 2.328519.

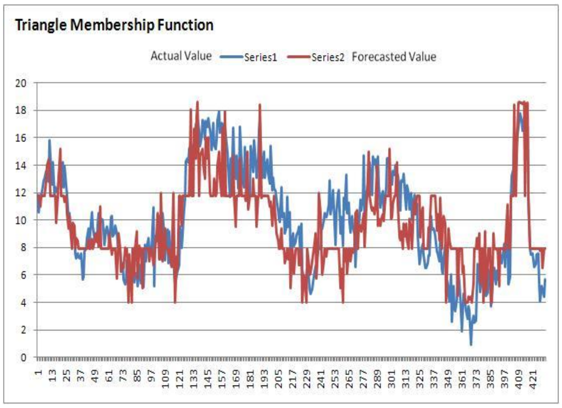

Fig.5. The comparison between the simulated and actual values of wind speed considering the triangular-trapezoidal membership function

Afterward, the wind speed prediction is performed using the Gaussian membership function. Fig.6 depicts the results of simulated wind speed in comparison with the real data. The mismatch value in this case equals 2.047703.

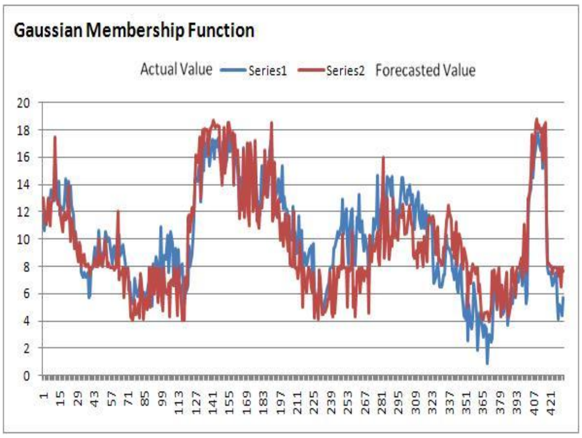

Fig.6. The comparison between the simulated and actual values of wind speed considering the Gaussian membership function

Now, it is investigated that which of the above simulations parameter have more important role in the forecasting approach and should be analyzed more noticeably. For this subject, the prediction results of previous sections are compared. Also, the fuzzy rules used in the predictor are changed in order to compare with the result of main predictor.

Primarily, assuming the fixed domain intervals regions, the shape of membership function is changed. 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 0.014 while it was 0.29 between the GBell and triangular-trapezoidal membership functions. (As discussed previously, two membership functions including the Gaussian and G-Bell are proposed for predictor due to the situation of membership function optimization. In this case, the predicted values of these functions are close to each other and a trivial mismatch of 0.014 can be observed.)

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 Fig.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 other in the most regions.

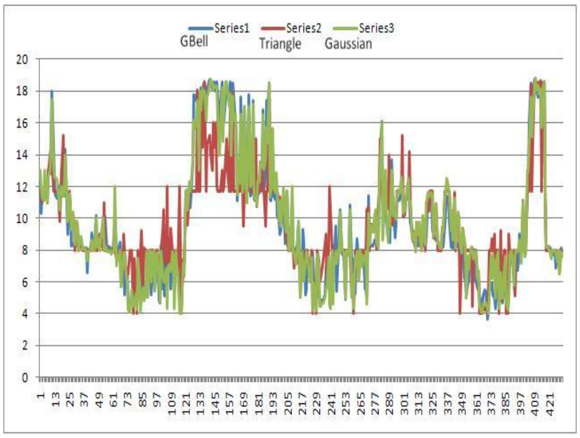

Fig.7. Comparison of wind speed simulation for various membership functions

For analysing and assessment of changes in domain intervals of regions, the G-Bell shape is selected and the most possible variations for domain interval of regions are generated. 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, It is obvious that the determination of domain intervals of region is more important. These intervals must be set precisely. In the first case, the intervals were adjusted considering the average of input data in which the variance of input data was considered and the best results were obtained in outputs. Wind speed predictions with different domain intervals of regions are illustrated in Fig.8.

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 Fig.9 for the simulated and actual wind speeds in these two cases.

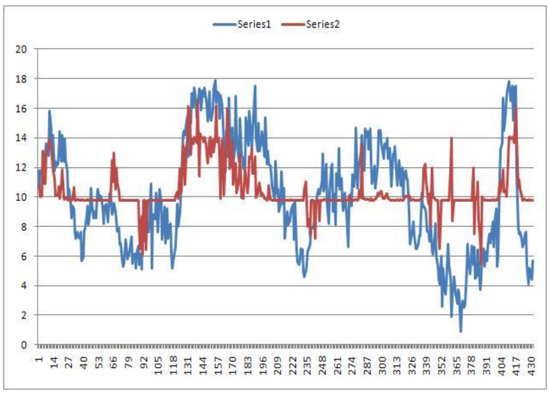

Fig.8. Comparison of wind speed simulation for various domain intervals

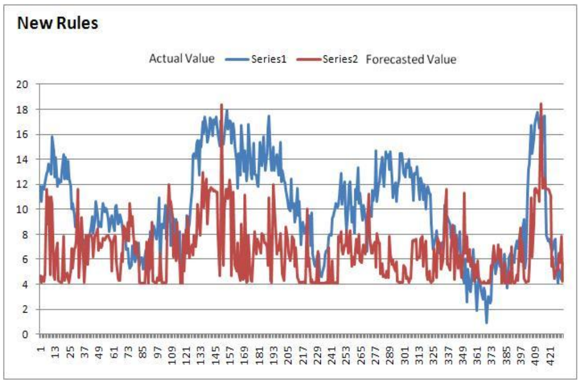

Fig.9. The comparison of simulated and actual wind speeds by changing the fuzzy rules

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.

Two 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:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(Actual\ Value_i - Forecasted\ Value_i)^2}{n}}$$

(2)

And the second is the mean absolute error that can be defined as below:

$$MAE = \frac{\sum_{i=1}^{n}\left|Actual\ Value_i - Forecasted\ Value_i\right|}{n}$$

(4)

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.1.

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.

Table.1.
The mismatch values for wind speed prediction by various criteria for different cases of membership functions, domain intervals and fuzzy rules

Cases \ Criteria	RMSE	MAE
GBell membership function	2.033413	1.614815
GBell membership function with variation in placement	2.428679	1.980671
GBell membership function with variation in domain interval	3.076392	2.558343
GBell membership function with variation in configuration	2.064571	1.660178
GBell membership function with variation in fuzzy rules	4.896524	4.040166
Triangular-trapezoidal membership function	2.328519	1.952326
Gaussian membership function	2.047703	1.647685

4. Conclusion

In this paper, the modelling and forecasting of the wind speed for the future year has been done using the real data gathered in the previous year. A new approach was proposed for selecting the optimal membership function. In this method, unnecessary iterations of trial and error method are avoided and the best solution is achieved in the fast way. The obtained results show that this method consumes less time and has more performance in wind speed prediction. The advantage of the proposed prediction fuzzy 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.

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 analysed. For this purpose, the type and formations of membership functions, the domain intervals region of the fuzzy system, and the fuzzy rules have been changed by doing sensitivity analyses. The results demonstrate that the proposed optimal membership function presents the best results for prediction. The most error occurred in the case of variations of “Then” part of 10 fuzzy rules to a lower level. In this case the error was three units more than the error in the previous case. 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 mismatches in wind speed prediction, it is proposed to add the inputs of the system. In other words, more factors are considered for wind speed modelling. So, the wind speed modelling will be surely more accurate and the prediction will be done more precisely.

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