Fuzzy-C Means Clustering Based ANFIS wind speed forecast

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***Abstract* - Wind Energy is now becoming a widely used renewable source of energy for the restructured Power system operations around the world through Electric utilities. Unpredictability and instability of wind speed and wind power are the key problems with wind power generation. For solving the underlying problems, wind speed forecasting is essential. A lot of investigation has been going on over the last few years to predict wind speed with reduced prediction errors. This article introduces a new clustering approach based on a wind speed prediction based on the Adaptive-Neuro Fuzzy Inferencing Scheme (ANFIS). For the forecast, the original wind speed data for a month is used. The clustering is done with Fuzzy-C Means (FCM) algorithm. We like to specify that, we have taken user modified IEEE-30 Bus system for validation. The proposed FCM– ANFIS method proved to be better by comparing the Root Mean Square Error (RMSE) with the existing methods.**

Index Terms - Wind Speed Forecast, Adaptive Neuro Fuzzy Inference System (ANFIS), Root Mean Square Error (RMSE), Fuzzy-C Means clustering (FCM).

I. INTRODUCTION

Wind power, in many countries in Europe, North America, Africa, is one of the fast-growing sources of electricity and Middle-East due to the abundance in the availability [1, 2]. The importance of generation of electric energy with wind generators is due to the increased stress on the use of renewable source of energy [3]. Wind energy is the cleanest form of resource and can be harnessed at the lowest cost. The contribution to the world energy requirement is increasing due to its immense advantages that many researchers are finding the best way to utilize the available wind energy for the better economy of the nations.

The wind generated is highly based on the seasonal changes, location terrain and the weather pattern of a particular area [4]. Major problem faced in wind based power generation is intermittency, unpredictability and irregular nature of the wind. If wind generators have to be set up, reliability can be assured only if the wind speed is previously known or a similar pattern is forecasted. This is where the wind speed forecasting plays an important role [5]. Wind Speed forecasting has both its practical value in meteorology and scientific research [6]. The wind speed forecasting contributes major role in restructure market so that day ahead scheduling of wind generated electric power can be carried out.

Many scientific research works related to the wind speed forecasting has been carried out. Various forecasting approaches have been recommended in the last few decades. Two types of models were developed which are probability based modeling and approximate reasoning-based modeling. The time series models are most suitable statistical models developed which includes Auto Regressive (AR) and Auto Regressive Moving Average (ARMA) models [7, 8]. These methods were used for short-term wind speed prediction. Wind speed was forecasted by stochastic modeling techniques but faced many difficulties [9]. The rules are fixed and it failed to have adaptability and decision-making capacity.

Recently forecasting of wind speed is initiated by the implementation of soft computing techniques such as Artificial Neural Network (ANN) and Fuzzy logic and evolutionary algorithm. These techniques have their own advantages and disadvantages. The ANN becomes difficult to train for a large system. Fuzzy Logic does not have a self-learning capability. Building a rule base for a complex system requires great amount of research.

This paper presented a wind forecasting model based on ANFIS and has shown superiority to neural network methods in time taken for learning and the accuracy in forecasting. ANFIS integrates the advantages of fuzzy logic and ANN. Fuzzy logic has good decision-making capability and maps the input and output based on the rule base. The ANN has good self-learning capability that recreates a system. In ANFIS fuzzy rules are automatically extracted from the numerical data. By the self-learning ability, the ANFIS adaptively adjust the membership functions. Few ANFIS based researches have been proposed in the past but implementation of the same for wind forecasting is innovatively applied and the results are projected in this paper. But due to the unpredictability and irregular nature of wind, error will be still present between the predicted and forecasted wind values.

In order to bring the Root Mean Square Error (RMSE) value to a much lower value data clustering can be introduced. A clustering based on fuzzy logic is been presented here to first cluster the large collected value of wind speed. Clustering is basically dividing the data into homogeneous groups such that similar data are grouped into the same group or clusters. In clustering there are two types such as the hard Means clustering (K Means algorithm) and (FCM). In hard clustering each data belongs to a single cluster. The membership function of each data can belong to more than one cluster in FCM clustering. The membership feature indicates how often each data forms part of a cluster. The degree of membership defines the extent to which each cluster belongs.

Thus, a data under each cluster is similar to each other and hence when this is then given to ANFIS for prediction much better result will be obtained. More accuracy, less RMSE, reliable forecasting can be expected. In this paper FCM clustering algorithm based ANFIS forecast is presented. The simulation is carried out in MATLAB. The results show the superiority of using Fuzzy-C Means algorithm with ANFIS for wind speed forecasting. The following section converse the proposed solution methodology. We have taken user modified IEEE-30 Bus system for validation. The data are not disclosed in this paper due to the limitation on number of pages. The implementation of wind speed prediction with the mentioned methodology is presented in the later section of the paper.

II. Solution Procedure

A. Fuzzy – C Means Clustering (FCM)

In FCM, related data are clustered together on the basis of the membership grade, indicating to what degree each data is part of a cluster. The system is first presented with a wind speed data set and based on the clusters required, the cluster centers are found. The cluster centers once found are later on used in the iterative algorithm.

The real time data of wind speed for 720 hours i.e. 30 days of a month with 24hours of each day is collected. Wind speed data is collected for each hour. Related wind data is grouped together to form a cluster during the clustering process. There are differences in the wind speed data between different clusters. Data points in the fuzzy cluster population imitate more than one cluster. The extent to which the data points associated with each cluster are specified by membership grade. An iterative optimization with updated cluster centres (C_j) and membership (μ_{ij}) is used to carried out partitioning. This objective function is provided below,

$$F_m(U) = \sum_{j=1}^{C} \sum_{i=1}^{N} (\mu_{ij})^m \|X_i - C_j\|^2 \quad (1)$$

Where, U is the membership function matrix, m is any real number greater than 1 and is a constant to control fuzziness. M_{ij} is the degree of membership value of X_i in the cluster group j, X_i is the i^{th} of wind speed measured data and C_j is the center of all the available clusters in the cluster.

The objective Function is selected with the following constraints,

$$\left.\begin{array}{l} M_{ij} \in [0,1] \quad i = 1, \dots N, \ j = 1, \dots \\ \sum_{j=1}^{C} \mu_{ij} = 1 \quad i = 1, \dots N \\ 0 < \sum_{i=1}^{N} \mu_{ij} < N \quad j = 1, \dots C \end{array}\right\} \quad (2)$$

The iteration will stop when $\max_{ij}\{|U^{(k+1)} - U^{(k)}|\} < \varepsilon$, where, ε is a tolerance level and k is the iteration stage. This process shall converge to a local minimum F_m. The algorithm is presented with the following steps.

Step 1: Initialize the function U = [μ_{ij}] matrix, $U^{(0)}$

Step 2: At k-step start calculate vectors $C^k = [C_j]$ with $U^{(k)}$

$$C_j = \frac{\sum_{i=1}^{N} \mu_{ij}^m \times X_i}{\sum_{i=1}^{N} \mu_{ij}^m} \quad (3)$$

Step 3: Update the membership measure.

$$M_{ij}^m = \frac{1}{\sum_{k=1}^{C} \left(\frac{\|X_i - C_j\|}{\|X_i - C_k\|} \right)^{\frac{2}{(m-1)}}} \quad (4)$$

Step 4: If $\max_{ij}\{|U^{(k+1)} - U^{(k)}|\} < \varepsilon$ then stop; else return to Step 2.

B. Adaptive Neuro Fuzzy Inference System (ANFIS)

The decision-making of the FIS and the learning capabilities of the neural network are integrated in the non-linear ANFIS technique. ANFIS combines the benefits of a fuzzy system and a neural network system that are interpretable and adaptable. The hybrid learning technique is used here which provides fuzzy modeling to learn the wind speed data in order to determine the membership function that will map more accurately input-output data. ANFIS is trained faster when compared to the artificial neural network. For ANFIS, the Sugeno fuzzy model is decided with two inputs and one output. The rule for the Sugeno type model is shown below.,

Rule i: It is decided that x is A_i and y is B_i

Then $f_i = p_i x + q_i y + r_i$ (5)

The structure of the ANFIS model is shown in Fig 1, which has five different layers and each layer depicts a particular function. Layer 1 depicts fuzzification of the input data. The values of the Neuron are given by parameters of membership functions. The typical membership function is given in the equation 7 where a_i, b_i, c_i are the premise parameters. Output from the first layer is the membership function given by $O_{1,i}$.

$$O_{1,i} = \mu A_i(x) \quad \text{for i = 1, 2} \quad (6)$$

$$\mu A(x) = \frac{1}{1 + \left|\frac{x - c_i}{a_i}\right| 2b_i} \quad (7)$$

Layer 2 represents the threshold at which the triggering of fuzzy rules which is calculated using the soft-min or product operators take place. Every node in this layer is labelled as Prod. Output is the multiplication of all input signals. Each node represents the force of the state.

$$O_{2,i} = w_i = \mu A_i(x) * \mu B_i(y) \ \text{for i = 1, 2} \quad (8)$$

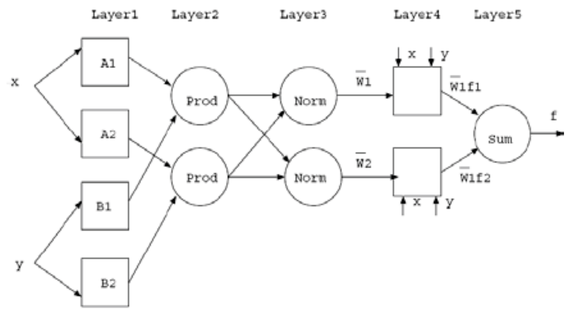

Fig. 1 Structure of ANFIS

In Layer 3 standardization (arithmetic division) operation is carried out. Each node of this layer is defined by the Standard. The ratio of the firing force of the i^{th} law to the sum of all the rules is determined for the i^{th} node. Normalized firing strengths are referred to as outputs as shown below.

$$O_{3,i} = \overline{w} = \frac{w_i}{w_1 + w_2}, i = 1,2 \quad (9)$$

The consequent part of the Layer 4 is obtained using the linear regression or Using the normalized activation level product and the user specified rule performance. Each node is an adaptive node of this layer identified by the role of the node. The consequent parameter of this node is represented by p_i, q_i and r_i.

$$O_{4,i} = \overline{w_i} f_i = \overline{w_i}(p_x + q_i y + r_i) \tag{10}$$

The algebraic sum of all the rules and their respective outputs shall be considered in order to obtain the ANFIS output of layer 5. A single node of this layer is called as sum and calculates the total output as shown below.,

$$\text{Overall output} = O_{5,1} = \sum \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{11}$$

The ANFIS parameters are optimized in two steps first the premise parameter is designed and then the consequent parameter is trained. The premise parameters are designed by different methods. The premise parameters are first set and then the parameters affecting the values are obtained with the help of Hybrid Learning rule. This rule is constructed using the combination of both gradient descent and least square estimation algorithm. The gradient descent algorithm channelizes the membership function parameter. Least square estimation algorithm aids to learn the consequent parameters.

III. RESULT AND DISCUSSION

Firstly, the wind speed data for a month is collected from potential wind Station at Leeuwarden in the year 2006 [27]. The wind speed is measured at 10.0-meter height the wind speed data for each hour is obtained. 720 hours wind speed data are collected and is shown in Fig 2.

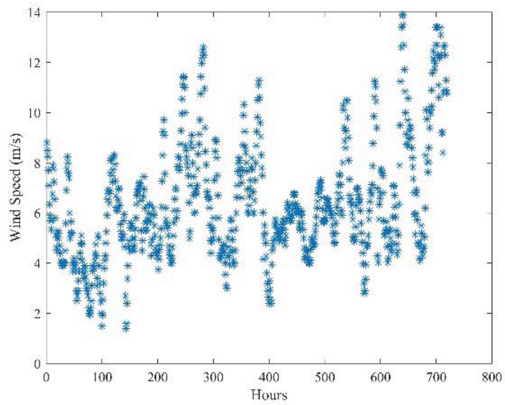

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Fig. 2 Collected wind speed data for 720 Hours

Thus we see that the nature of the wind speed data is irregular and stochastic in nature. The Histogram distribution of 720 wind speed data is represented in Fig 3. Most of the wind speed lies within 4-7 m/s.

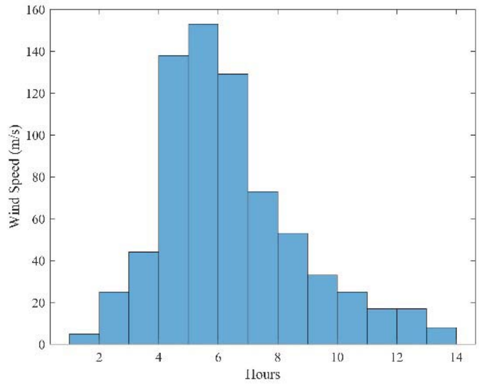

Fig. 3 Histogram Distribution of 720 Hours Wind Speed Data

If the obtained wind speed data were given directly to ANFIS the RMSE will be very high. Hence the FCM algorithm is used which will cluster data into groups. Similar data are clustered together. FCM algorithm minimizes the objective function meeting the constraints with the addition of the latest value to the membership (μ_{ij}) and the cluster centers (C_j).The objective Function versus the Iteration count is shown in Fig 4.

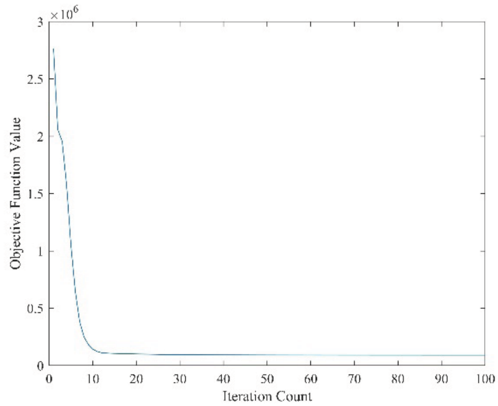

Fig. 4 Convergence of Objective functions

It is observed by the 100th Iteration notes that objective function is reduced at the lower iteration value and stays constant. Cluster segregation is accomplished with a modified membership function, by iterative optimization of the μ_{ij} and the C_j, the 720 data are clustered into 15 clusters.

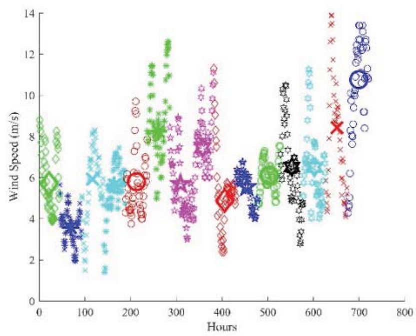

Fig. 5 Clusters created by FCM algorithm

The 15 clusters obtained by FCM is shown in the Fig 5. Similar range of values are clustered together into clusters. Now each cluster is used to train ANFIS. The RMSE will be reduced while training and better forecast with ANFIS will be obtained and plotted which clearly shows the importance of using Fuzzy-C Means method.

Wind Speed Forecasting is carried with ANFIS which is close to accurate. The uncertainty in power scheduling can be reduced by accurate wind speed prediction. Each cluster of wind speed data is given to ANFIS to forecast the wind speed of each cluster. The gaussian bell membership functions are considered, the simulation has been attempted by a number of membership functions. For all the developed clusters, the number of membership functions is selected as 5 based on many trials. It will lead to increased training time if the number of MFs is increased. The ANFIS model training was carried out in the MATLAB. Thus all the 15 clusters are trained by 15 ANFIS network. Each ANFIS network is trained till the ANFIS plots the training error against the epoch curve as 15 clusters of wind speed samples are trained in Fig 6.The step-size profile for 15 clusters is shown in Fig 7. The size of the move is increased by a certain amount if the measure of error decreases four times in a row.

After epochs of training ANFIS of each cluster, the final MFs for each cluster are shown in the Fig 8. The actual wind speed and the ANFIS forecasted wind speed for the 15 clusters are shown in the Fig 9.

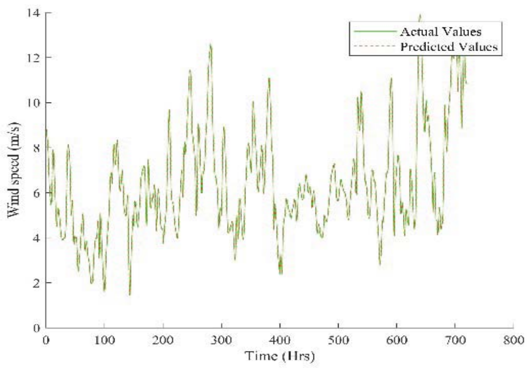

Fig. 10 Actual and ANFIS Predicted Wind Speed for 15 clusters

We see that both the actual and ANFIS predicted values are close to each other for all the 15 clusters of wind speed data. The error which is the difference between the actual and ANFIS predicted wind speed data is evaluated and represented in the Fig 11.

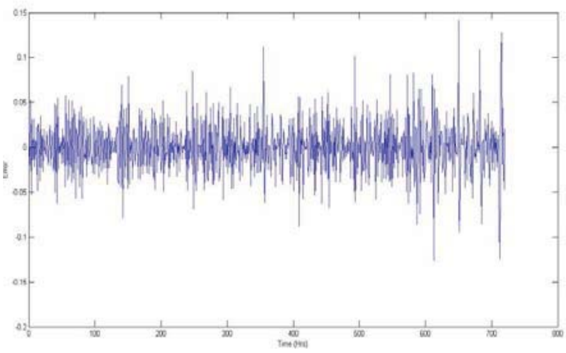

Fig. 11 Error between Actual and ANFIS Predicted Wind Speed

Thus, the reliability, accurate prediction of wind speed obtained is evident with help of ANFIS. If the 720 wind speed data were given to the ANFIS without clustering the RMSE value would be large and accurate prediction of wind speed will not be possible. The conventional statistical models developed are time series models which include AR and ARMA models.

IV. CONCLUSION

Wind speed Forecasting is a necessity for reliable Electrical Power generation and Restructured Market. The irregular pattern of wind speed in a particular locality has made it difficult to set up wind farms in order to utilize the wind energy. we have taken user modified IEEE-30 Bus system for validation. In this paper 720 Wind Speed data considering each hour of everyday for a month is taken. The wind speed hourly data are random and do not follow a regular pattern. Hence for better accuracy of wind speed forecast using ANFIS the 720 data collected are first clustered using FCM algorithm is implemented and 15 clusters of wind speed are created. Thus similar data are grouped together which makes ANFIS to forecast wind speed with reliability. The ANFIS is trained for each cluster till the error reduces to an acceptable value. The RMSE value of the presented method was found to be 0.7 compared to 0.85 for AR and 0.8 for ARMA models. From the result it is visible that RMSE is reduced to a very low value that the actual and forecasted wind speed values are in close accordance with each other. Thus, unpredictability and unreliability in the pattern of wind speed is over come with FCM-ANFIS based wind speed forecast.

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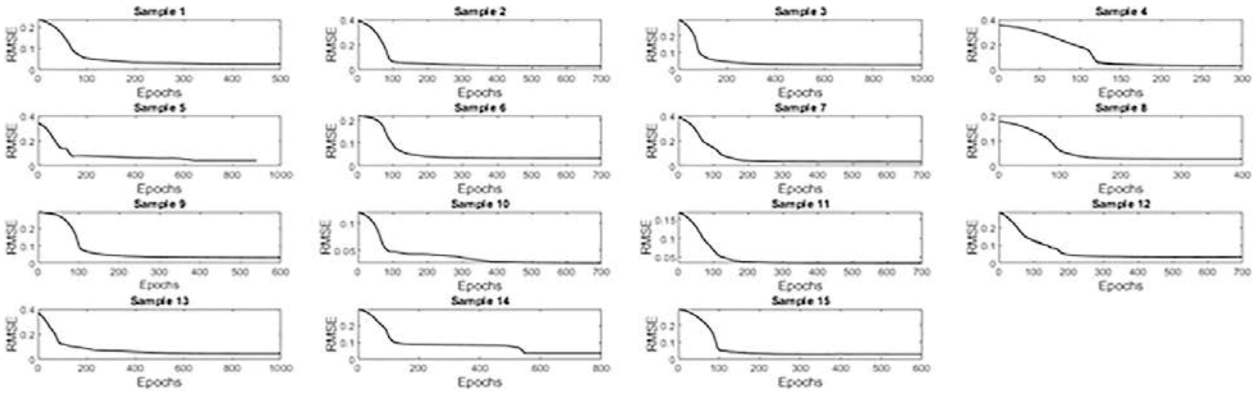

Fig. 6 Error Plot of ANFIS for 15 clusters

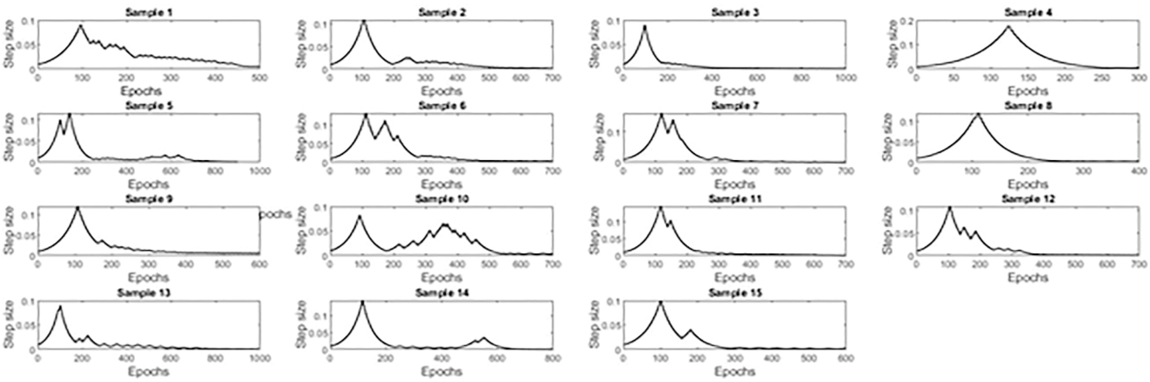

Fig. 7 Step Size Plot of ANFIS for 15 clusters

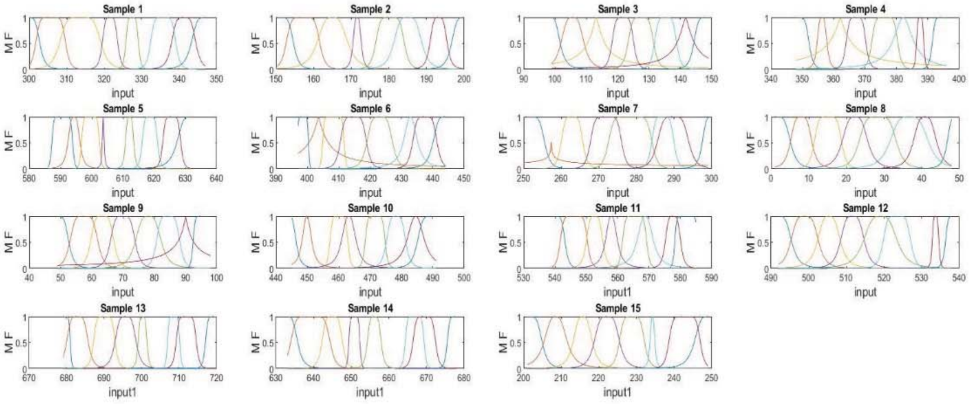

Fig. 8 Final Membership function for 15 clusters after training for 15 clusters

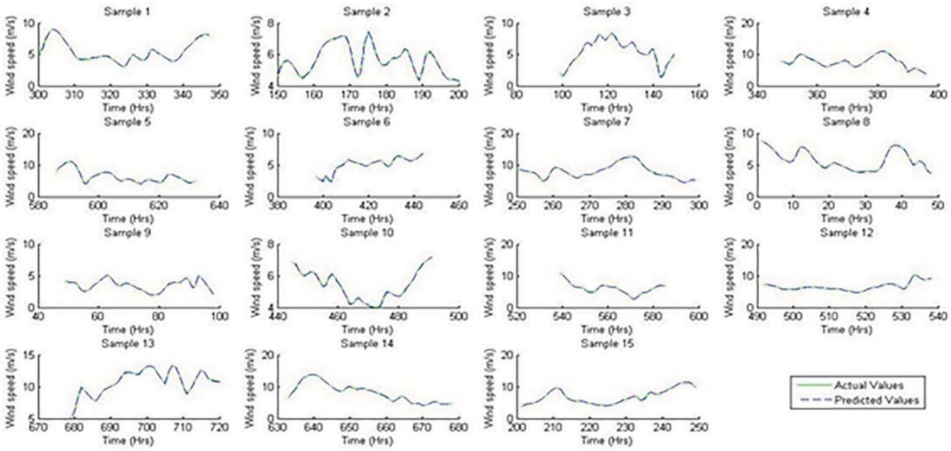

Fig. 9 Actual and ANFIS Predicted Wind Speed for 15 clusters