Average Hourly Wind Speed Forecasting with ANFIS

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ABSTRACT

Wind energy is increasing its participation as a main source of energy in power grids and electric utility systems around the world. One of the main difficulties of integrating large amounts of wind energy in power grids is the natural intermittency of its generated power [1, 2] due to the energy produced from the wind turbine being dependent on the availability of the wind, which is highly stochastic in nature. To address this problem, more accurate and reliable wind power forecasting techniques have been proposed [1, 2]. This paper explores a new approach using Adaptive Neuro-Fuzzy Inference Systems (ANFIS) to forecast the average hourly wind speed. To determine the characteristics of ANFIS that best suited the target wind speed forecasting system, several ANFIS models were trained, tested and compared. Different types and number of inputs, training and checking sizes, type and number of membership functions and techniques to generate the initial Fuzzy Inference Systems (FIS) were analyzed. Comparisons of the different models were performed and the results showed that the 4 inputs models generated by grid partitioning and the 6 inputs models generated by subtractive clustering provided the smallest errors with the models using wind speed and air pressure as inputs having the best forecasting accuracy. Since using different variables that are correlated with wind speed provided the best overall results, recommendations are provided for continued research into this area.

1 INTRODUCTION

Energy is an integral commodity of life and the extent of its importance is reflected by the need for it in every activity of modern day life. Today, much of our energy demands are met by fossil fuels [2, 3] – a non-renewable source of energy which would eventually be depleted. It is this problem of fossil-fuels added to the environmental ill-effects of its power plants that have spurred human interest into the acquisition of renewable sources of energy such as wind energy. Apart from its abundance, wind power is economically competitive and provides a plethora of benefits to the environment [3]. These advantages have made wind power the fastest growing power generation sector in the world with a global cumulative installed capacity increase from 93 GW in 2007 to 121 GW in 2008[3, 4].

However, one of the shortcomings in the wide use of the generation of electricity from the wind is the intermittency of the availability of the wind which determines the extent to which energy is produced from the wind turbine. This problem is exacerbated by the fact that wind energy cannot be stored and cannot be easily ramped up to meet load requirements [1, 5, 6]. To address these problems, accurate and reliable very short-term wind forecasting ranging from a few minutes to the next hour has been suggested [1, 2, 3, 5, 6, 7].

For power systems with high wind penetration, wind predictions would improve the reliability of the system as it can allow utility planners to determine the required number and size of wind plants and reserve fossil fuel generators to serve the load and substantially support the optimal operation, planning and management of power systems, thus allowing utility operators to maintain the balance of the system [7].

It may be agreed upon that wind power can be a more viable prediction parameter than wind speed for power generation purposes on the premise that predicting wind speed and converting it to power output using power curves or the following equation which relates the wind turbine's power output to wind speed:

$$P = \frac{1}{2}(C_p)*(\rho)*(A_b)*(v_w^{3}) \tag{1}$$

(where C_p is the coefficient of performance, ρ is the air density, A_b is the area swept by the blade and v_w is the wind speed at right angles to the turbine's blades-face), can possibly provide less accurate prediction results when compared with forecasting wind power directly, due to the incapability of the curve and equation in capturing the true dynamics of the wind turbines [6, 7]. However, forecasting wind power has its limitations since it can be linked to a particular machine design or operation and therefore, is more likely to become invalid or obsolete than wind speed forecasts, when generators have to be replaced or new power operating systems are installed. In addition, apart from the wind speed predictions being a more logical approach in beginning to understand wind forecasting techniques for power generation, it is easier to obtain a less corrupted data set for wind speed than power output and compensations in the short-comings of the use of power curves and equations in converting wind speed to wind turbine power output can be made through aggregate forecasting [6].

2 Current Wind Speed Forecasting Methods

The main techniques that are currently available and considered as industry practices are the Numerical Weather Prediction (NWP), Persistence and the Statistical and Artificial Neural Networks (ANN) methods.

2.1 Numerical Weather Prediction Method

This meteorological-based technique uses as inputs the current weather conditions into a 4 dimensional (longitude, latitude, elevation and time) grid model of the location of study and applies conservation equations (mass, momentum, etc.) at different places to predict changes in the wind [5]. According to Negnevitsky et al. [5], NWP models were originally designed to perform forecasting for large area weather patterns over many countries and for long time scales ranging from several hours to months ahead. Therefore, if the NWP models are to be used for the very short term forecasting time scale required by power systems for wind power generation [8], the resolution of the grid must become greater. However, as the resolution increases, the grid becomes more detailed with topographical characteristics such as forests and towns which may undergo changes. Since the NWP models mimic the place of interest, any changes in the real system would require the remodeling of the NWP models in order to produce accurate results [5]. This then makes the implementation and maintenance of NWP models for very short term wind speed forecasting time scale more costly.

Besides the cost factor, the problem of the length of time taken to provide forecasts for the NWP method arises. NWP models are complex mathematical models and therefore to perform the tedious calculations required to solve these equations demands great computational effort through the use of supercomputers and even with these tools, the time taken to produce results limits the NWP's ability to provide very short-term wind speed forecasts for power generation.

Even though the NWP method may be costly and time consuming, it provides more accurate results for forecasts of time steps ranging from one hour and beyond.

2.2 Persistence Method

A tool developed by meteorologists to supplement the NWP forecasting system, is the simplest way to perform wind forecasting [7]. This model works on the basis that there is a high correlation between the wind speed in the immediate future and the current wind speed. That is, the wind speed at time, t is the same at the time, t + x [1, 7] in the future. Milborrow [9] stated that Persistence is more effective than NWP in some predictions ranging from several minutes to hours. As expected, the accuracy of this model degrades rapidly with increasing prediction lead time. However, it tends to be more robust than the NWP method in this regard [9].

2.3 Statistical and Neural Networks Methods

The statistical and neural networks methods are projected for forecasting time steps ranging from minutes to one hour [5]. Negnevitsky et al. [5] concluded that one of the reasons for these methods' success at these time steps is that they both use the current wind speed at the location of interest as one of the inputs into the system.

The main difference between the statistical and neural networks method lies in the time span of the data used in the models' development. While the statistical method uses auto-recursive mathematical algorithms to find the difference between the predicted and actual values in the immediate past to tune model parameters [5, 6, 7], the neural networks method looks for patterns between input data and the output wind speed over a long period of time [5].

One of the disadvantages of these techniques is that their accuracy tends to degrade with increasing lead time; they begin to produce poor results for forecasts over 5 hours in advance [5, 9]. The difficulty of maintaining the accuracy of the wind speed forecasts as the prediction lead time increases can be attributed to the high probability of change in the wind speed in a short space of time.

3 Adaptive Neuro-Fuzzy Inference Systems

ANFIS is a hybrid of two intelligent systems: Artificial Neural Networks (ANNs) and Fuzzy Inference Systems (FISs). ANNs map an input space to an output space through a collection of layered processing elements called neurons that are interconnected in parallel by synaptic junctions. ANNs are developed by continuously passing real world system data from its input to output layer. For each pass of data, signals propagate from the input to output layer to produce an output which is compared to the desired output. The difference between these values is then used to adjust the synaptic connections so that the ANN can mimic the system the data represents. This procedure gives ANNs the capability of looking for patterns in the information presented to it, thus providing it with the advantage of learning about systems. FISs are based on fuzzy logic (a continuous range of truth values from 0 to 1), IF-THEN fuzzy rules and fuzzy reasoning (which can be likened to human reasoning through linguistic variables such as small, medium, large). These features of FIS allow it to make inferences using the rules and known facts to derive reasonable decisions [10, 11]. Thus the combination of ANNs and FISs to form ANFIS, integrates the benefits of the individual intelligent systems to form a superior technique that can optimally model the dynamics of difficult systems such as that of wind speed.

The ANFIS of interest is of a 6 layer feedforward neural network and of the Sugeno (Type III) FIS type. To understand the structure and operation of ANFIS in forecasting, a 2 input - 1 output ANFIS model is presented and its structure and operation is related to a generalized model. Figure 1 shows the ANFIS structure and Equations 2 to 5 are the rules for this model where the IF part of the rule is referred to as the antecedent and the THEN part is the consequent.

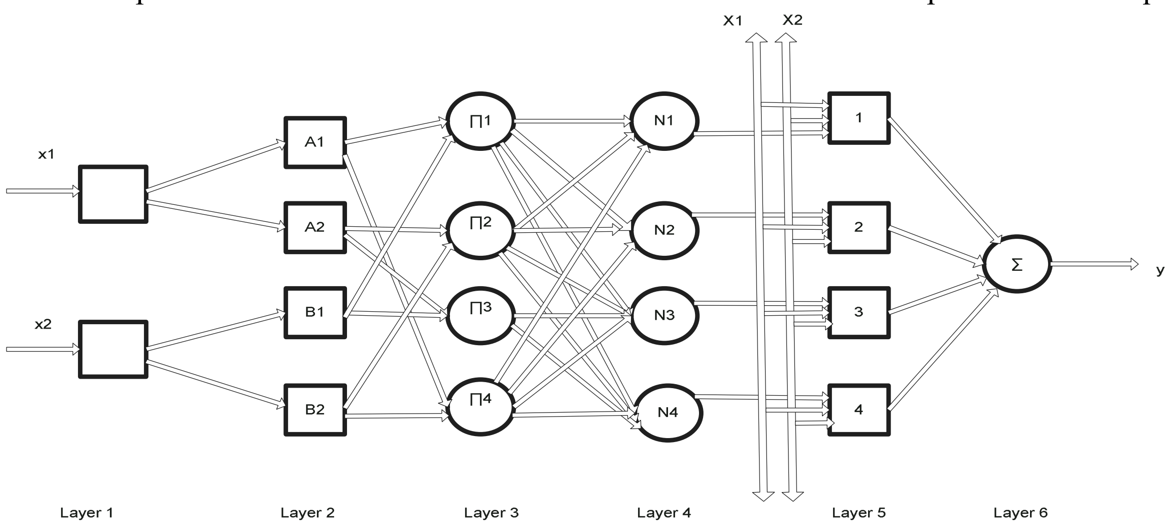


Figure 1: ANFIS Structure

Rule 1: If x is A_1 and y is B_1, then $f_1 = p_1x + q_1y + r_1$ (2)
Rule 2: If x is A_2 and y is B_2, then $f_2 = p_2x + q_2y + r_2$ (3)
Rule 3: If x is A_3 and y is B_3, then $f_3 = p_3x + q_3y + r_3$ (4)
Rule 4: If x is A_4 and y is B_4, then $f_4 = p_4x + q_4y + r_4$ (5)

In general, an n-input, 1-output ANFIS model is an n + 1 dimensional input-output space. Therefore, a 2 inputs-1 output ANFIS model is a 3-dimensional input-output space. In order for ANFIS to be used to model a system, data that is representative of the target system must be presented to ANFIS. The entry of raw data or **crisp inputs** from the target system into ANFIS corresponds to layer 1 – the **input layer** in Figure 1.

Since the Neural Network classifies data and looks for patterns within it, then when the input data is in the 3-dimensional space, it is classified into groups called fuzzy spaces. To do this, the crisp inputs are compared with membership functions in the antecedent of the rules of ANFIS, to determine the degree to which the inputs, in this case, X1 and X2 belong to fuzzy sets A_i and B_i respectively. The degree to which the inputs lie within the fuzzy space is given a value between 0 and 1. This process is known as **fuzzification** and takes place in layer 2, the **fuzzification layer.** Each node in this layer is adaptive and is given by:

$O_{2,i} = \mu_{Ai}(x1)$ for i = 1, 2 (6)
$O_{2,i} = \mu_{Bi-2}(x2)$ for i = 3, 4 (7)

where i represents the node of ANFIS and, μ_{Ai} and μ_{Bi-2} are the antecedent membership functions which can be any parameterized function such as the bell-shaped function given in Equation 8:

$$\mu_{Ai}(x) = \frac{1}{1+\left[\left(\frac{x-c_i}{a_i}\right)^2\right]^{b_i}} \tag{8}$$

a_i, b_i and c_i are the **non-linear or premise** parameters of the antecedent of the rules.

Once the locations of the inputs in the fuzzy spaces are identified, then the product of the degrees to which the inputs satisfy the membership functions is found and can be mathematically expressed by Equation 9. This product is called the **firing strength** of a rule and is represented by layer 3, the **rule layer** where each node in this layer is fixed and represented by a rule.

$$O_{3,i} = w_i = \mu_{Ai}(x1)\ \mu_{Bi-2}(x2) \quad \text{for } i = 1, 2, 3, 4 \tag{9}$$

Each fuzzy space is governed by an ANFIS rule where the antecedent of the rule defines a fuzzy space in the input space [11]. For ANFIS, there are M^n fuzzy rules where M is the number of membership functions per input and n is the number of inputs [11]. Hence, for the ANFIS model of study in this paper where there are 2 membership functions per input, there are 4 fuzzy rules. The implication of the role of this layer is that the firing strengths give an indication of which rule may be most applicable to the inputs.

In layer 4, the **normalization** layer, the ratio of each rule's firing strength is calculated with respect to the sum of the firing strengths of all the rules. Each node in this layer is fixed and its output is given by Equation 10:

$$O_{4,i} = \bar{w}_i = \frac{w_i}{w_1 + w_2 + w_3 + w_4}, i = 1,2,3,4 \tag{10}$$

In layer 5, the **defuzzification** layer, the output of each node is the **weighted consequent value** given by Equation 11:

$$O_{5,i} = \bar{w}_i f_i = \bar{w}_i (p_i x_1 + q_i x_2 + r_i), i = 1,2,3,4 \tag{11}$$

where p_i, q_i and r_i are called **linear or consequent parameters** of the fuzzy rules. The consequent of the ANFIS rule defines the output in the fuzzy space. Each neuron in this layer is connected to the respective normalization neuron and inputs X1 and X2.

Layer 6 is the **summation layer** and its output which is the sum of all the outputs of the layer 5 is represented by:

$$O_{6,i} = \sum \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}, i = 1,2,3,4 \tag{12}$$

This gives the overall output for the respective inputs within the fuzzy space.

The most fundamental component of ANFIS is its IF-THEN rules which are defined by its premise and consequent parameters. The IF-THEN rules tell where in the fuzzy space the output lies for the given inputs.

Before the ANFIS system can be used for prediction, the parameters of the rules are determined by first generating an initial FIS where random values are assigned to the parameters and then applying an optimization scheme to determine the best values of the parameters that would provide rules that would idealistically model the target system. After training, the rules remain so that when new input data is presented to the model, the rules provide a corresponding reasonable output.

The optimization technique is a learning algorithm which uses data (training data) from the target system to generate signals that propagate backwards and forwards and update the parameters by a process known as training. The learning algorithm proposed for ANFIS is a hybrid learning algorithm that minimizes the error between the ANFIS model and the real system [10, 11]. ANFIS employs the least squares estimate and the gradient descent method in the hybrid learning algorithm. Once input-output data is presented to ANFIS, in one epoch the data is propagated forwards from one layer to the next until the fourth layer, and the least squares estimate is employed to update the linear or consequent parameters. An error is calculated and this is propagated backwards and the gradient descent is used to update the non-linear or premise parameters [1, 5, 6, 10].

4 DEVELOPING THE ANFIS WIND SPEED FORECASTING MODEL

In order to determine the characteristics of ANFIS that can ultimately provide the wind speed forecasting model with the best prediction accuracy the System Identification method proposed by J.S.R. Jang [11] was used**.** System Identification defines a mathematical model for a target system for which there isn't any *a priori* knowledge by observing its input-output data pairs. System Identification is broken down into two main steps: **Structure and Parameter Identification**. Structure Identification involves determining the type and number of inputs and membership functions that can best represent the target system to be identified while Parameter Identification involves finding the parameters of the rules that make up the ANFIS system. The application of System Identification to finding the best model involves repeatedly performing Structure and Parameter Identification.

To develop the wind speed forecasting models using ANFIS, the structure and parameter identification phases were broken down into a series of steps. The choice of these steps was influenced by the software (ANFIS Editor in MATLAB 7.0.1) that was available for the development process of the ANFIS wind speed forecasting models.

4.1 STRUCTURE IDENTIFICATION

This is the preparation phase for parameter identification and it primarily involves establishing the inputs for the ANFIS models and generating the initial FIS or the initial parameters that would be the starting point to finding the optimum model that would best fit the target system. Therefore, structure identification for this application was separated into (1) selecting the inputs, training and checking data for ANFIS and (2) generating its initial FIS.

4.1.1 Selection of inputs, training and checking data

Since there is no *a priori* knowledge on the wind speed system, then emphasis is placed on the only true and reliable information that is available on the target system which is embedded in empirical data collected from the wind speed system. This empirical data is represented by training, checking and testing data and the size, content and organization of these data sets are significant factors in determining the degree of accuracy of the ANFIS forecasting model. For this study, the data chosen for use was hourly averaged wind data. Hence, the minimum look-ahead period and therefore the time scale for forecasting wind speed was one hour.

Generally, there are two types of time series models that can be developed: **Univariate** and **Multivariate**. Therefore, ANFIS was designed to model univariate and multivariate time series where the **Univariate time series models** used current and past data on wind speed data alone while the **Multivariate time series models** used wind speed data along with data for variables that correlate with wind speed [12].

For the time series approach, data was collected from the target wind speed system and was divided into subsets where the number of components in each subset was dependent on the combined number of inputs and output. Each subset was of the general format:

$$\{\ldots,\ x(t-3s),\ x(t-2s),\ x(t-s),\ x(t),\ x(t+1s)\} \tag{13}$$

$\{\ldots,\ x(t-3s),\ x(t-2s),\ x(t-s),\ x(t)\}$ are the inputs into the system used to predict the point $x(t + 1s)$. $x(t)$ is the value of the time series at the present time, t and s is the chosen time scale.

To find the type of data to be used with the multivariate time series models, it was recognized that wind is generated by the difference in atmospheric pressure which is dependent on atmospheric temperature as exemplified by Equation 14 – the Ideal Gas Equation [13]:

$$P = \rho RT \tag{14}$$

P is the atmospheric pressure in Pa, ρ is the density of the air in kg/ m^3, R is a constant 287J/ kg ^oK and T is the temperature in ^oK. Therefore, to develop the multivariate time series model, wind speed data along with atmospheric pressure and temperature data were considered as viable inputs for the models. To determine which combination of inputs from wind speed, atmospheric temperature and pressure that would produce the best results, input selection was performed. Input selection, a heuristic method proposed by J.S.R. Jang [14] is based on the assumption that the ANFIS model with the smallest error after its first epoch of training has the greatest potential of achieving the lowest error when given more epochs of training.

According to Negnevitsky et al. [1], the training size is very important since it can affect the accuracy of the model given the stochastic nature of wind speed. Therefore, for ANFIS to properly model the wind system, it must be able to capture as many characteristics of the wind speed over time. To do this, a large training data set must be used. To evaluate the sensitivity of the ANFIS with respect to different training sizes, various amounts of data were used, starting with 6 months up to all the data available.

To ensure that the trained model is a proper representation of the target system, checking data is used [15]. The checking data works by looking for the point of overfitting of the ANFIS model. Overfitting occurs when the model is trained too much such that the mapping between the input and output data has lost its generalization capability to fit any data that it was not trained on [16]. Once the type of data that would best represent the target system was selected, the acquired data was then split into training and checking data.

Careful thought was given to the number of inputs used for the development of the ANFIS models as using a large number of inputs can considerably increase the length of time taken to train while at the same time allow a greater amount of information into the model with each epoch. The latter would result in more selective training and hence provide better prediction results [6]. Therefore, different ANFIS configurations with 7, 6, 5, 4 and 3 inputs were chosen.

4.1.2 Generation of the initial FIS

This step involves selecting a structure for the ANFIS model by determining the number of membership functions per input, type/shape of the membership functions for the premise part of the rule and the output membership functions for the consequent part of the rule. MATLAB 7.0.1 offers two methods for generating the initial FIS: Grid Partitioning and Subtractive Clustering.

A. Grid Partitioning

Once the grid partitioning technique is applied at the beginning of training, a uniformly partitioned grid which is defined by membership functions (MFs) with a random set of parameters is taken as the initial state of ANFIS. During training, this grid evolves as the parameters in the MFs change.

With the grid partitioning technique, the number of MFs in the premise part of the rules must be determined. Negnevitsky et al. [5] stated that a larger number of MFs better represents a complex system and therefore should produce better results. However, a large number of inputs or MFs in the premise part of the rules can produce a large number of fuzzy rules which can cause the learning complexity of ANFIS to suffer an exponential explosion. This is called the curse of dimensionality which can adversely affect the performance of ANFIS [11, 15, 16].

Not many literature papers have alluded to what is considered to be a large number of fuzzy rules. However, drawing on the experience of [11, 14] as a guide to choosing the number of MFs per input and since the largest number of inputs to be used was 7 then the smallest number of MFs that could produce overlapping while not invoking the curse of dimensionality is 2. The number of MFs was increased with one of the ANFIS models to get a greater understanding of the impact on the performance of ANFIS with this change.

In generating the initial wind speed forecasting FIS, by grid partitioning, the bell-shaped MF was favored over the other types since it offered more parameters which provided a greater number of degrees of freedom. The generalized bell-shaped MF is standard for ANFIS because of its smoothness and concise notation [5, 11, 15]. Other functions such as Gaussian and Trapezoidal were used as well to evaluate the performance with different types of MFs. For the consequent part of the rules the MFs responsible for defuzzification were the Sugeno type of first order. The output MF is chosen to be linear for the wind speed forecasting models since, the higher the order of output MFs, the greater is the likelihood of ANFIS fitting the target system [17].

B. Subtractive Clustering

This is one of the clustering algorithms used to categorize data into groups where the similarity is high for inter-group members and low for intra-group members. The subtractive clustering algorithm generates data clusters centers within the given data space by looking for data points that have the highest density measures. These cluster centers become the basis of the ANFIS IF-THEN fuzzy rules where the consequent MFs are of the first order Sugeno type and the premise MFs are Gaussian.

One of the advantages of Subtractive Clustering is that unlike Grid Partitioning, it does not invoke the curse of dimensionality, since the number of fuzzy rules produced depends on the number of data clusters which depends on how close the data points are in the input-output space. As a result, this technique can be used with a larger number of inputs. It was used to generate initial FISs for univariate and multivariate wind speed forecasting ANFIS models with 6 inputs.

4.2 *PARAMETER IDENTIFICATION*

Parameter Identification is the training of the ANFIS models through the application of an optimization scheme on the generated initial FIS. Training involves tuning the parameters of the ANFIS models, which determine the shape of the membership functions and ultimately dictates how the rules for the trained prediction models would behave. To train the ANFIS models, the optimization technique, error tolerance and the number of epochs are chosen.

The fuzzy logic toolbox provided two optimization methods: hybrid and backpropagation. To develop the ANFIS wind speed forecasting models, the hybrid technique was used since it is more popularly used with ANFIS than the backpropagation [1, 10]. In addition, it is regarded as the faster of the two techniques [1].

5 RESULTS

In accordance to the approach provided by J.S.R. Jang, different models were created by changing some part of its structure or parameters, and each was compared to the previous models created to determine if the changed characteristic provided better results. If the model produced better results, then these characteristics were kept and if not, the model was retrained with one of the characteristics of its structure changed. The models were divided into two groups according to the method chosen to generate the initial FIS: grid partitioning and subtractive clustering. After which, one feature of the chosen model: type of input data, size of training or checking data, type of membership functions or the number of membership functions per input was changed one at a time. The chosen structures were trained on data obtained from Meteorological Offices from the Caribbean and once trained they were evaluated using the performance metrics: RMSE and MAE.

The results from the models trained using the grid partitioning technique, showed the checking error curves for the different input models with 2 bell-shaped MFs per input trained on 6 months of wind speed data continuously increasing from the first epoch. An example of this is shown in Figure 3 for the 5 inputs model.

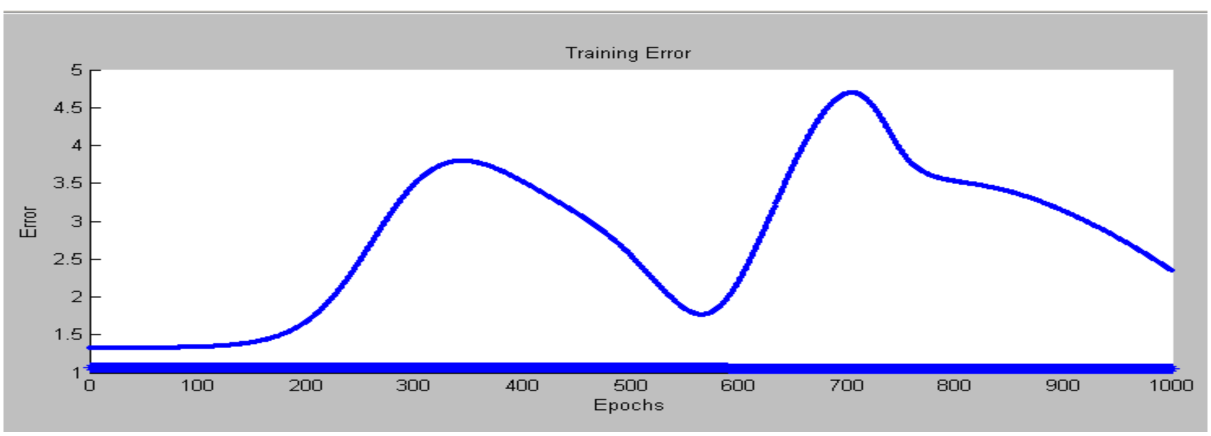


Figure 2: Training and checking error curves for the 5 inputs, 2 MFs per input model trained on 6 months of wind speed data (where RMS checking error is greater than RMS training error).

The analysis performed suggested that this amount of data was insufficient. While with the maximum available training data of 10 years, the training time for 1 epoch significantly increased (3.3s to 128s for 1 model), it was evident that more data can extensively improve the performance of the ANFIS modeling system. Comparing the periods of 3 and 10 years of wind speed data used to train a 4 inputs, 2 bell-shaped MFs per input model whose initial FIS was generated using grid partitioning, there was an increase in the error by 0.015 with the 10 years of data. Though this error may appear small, relative to the general changes in the errors that occurred with the changes in the models' configuration, this was a significantly large figure.

For the 1000 epochs of preliminary training with the 7 inputs model, the training took approximately 14 days and since these models have to be retrained to obtain optimum results, the 7 inputs model was not used further as its training time was too exhaustive. In addition, the 7, 6 and 3 inputs models did not give as good results as the other models. This can be attributed to the larger set of inputs having a larger number of fuzzy rules (even with 2 MFs per input) which invoked the curse of dimensionality associated with grid partitioning. The performance of the ANFIS model with 3 inputs supports Negnevitsky et al. [5] where the larger number of inputs allows greater passage of data with each epoch and therefore offers more enhanced model training, although it must be noted that Negnevitsky's proposition on the use of a large number of inputs should be recommended with the subtractive clustering technique.

The number and type of MFs were kept at 2 per input and of the bell-shaped type since the alternative options did not improve the models. Since the 4 inputs model performed better than the 5 inputs with the grid partitioning technique, this model was kept to produce the univariate and multivariate model. The best combination of inputs for the models trained on the multivariate time series was obtained with one of the inputs being wind speed and the other 3 as air temperature.

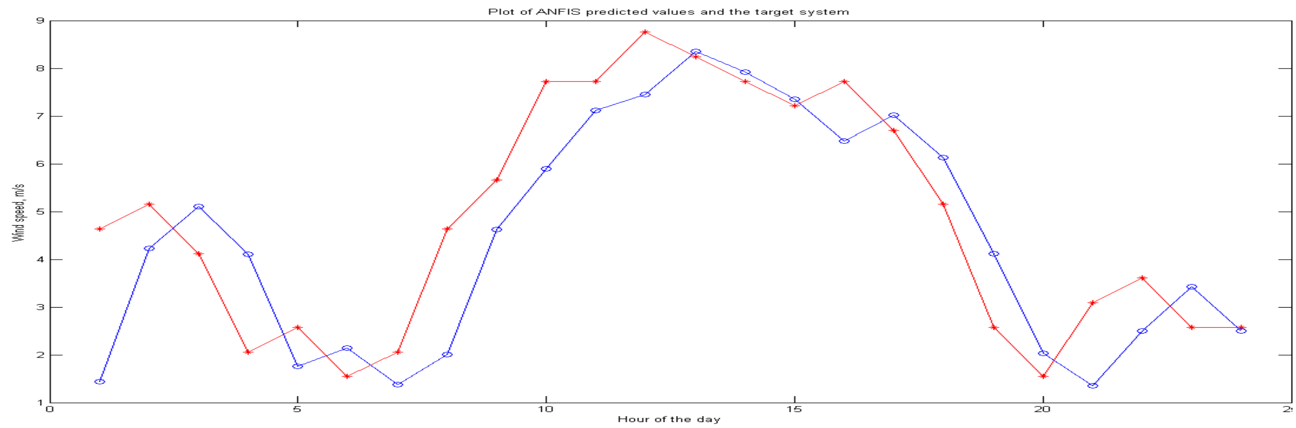
The models with relatively small number of inputs (4 inputs) produced better results if their initial FISs were generated using grid partitioning than by subtractive clustering. The larger number of inputs (6 inputs) produced better results and cost a shorter training period if their initial FIS was generated using subtractive clustering. This was a result of the subtractive clustering producing fewer rules than the grid partitioning technique. For example, with the 6 inputs univariate model generated by subtractive clustering, 8 fuzzy rules were produced opposed to the 64 rules created by the grid partitioning technique and though there were far fewer rules, the 6 inputs univariate and multivariate models performed just as well as the best models (4 inputs univariate and multivariate) generated by grid partitioning. The multivariate 6 inputs model with 1 input as wind speed and the other inputs as air temperature produced the smallest error on the first epoch after input selection was performed, thus reinforcing the high correlation between wind speed data and air temperature data.

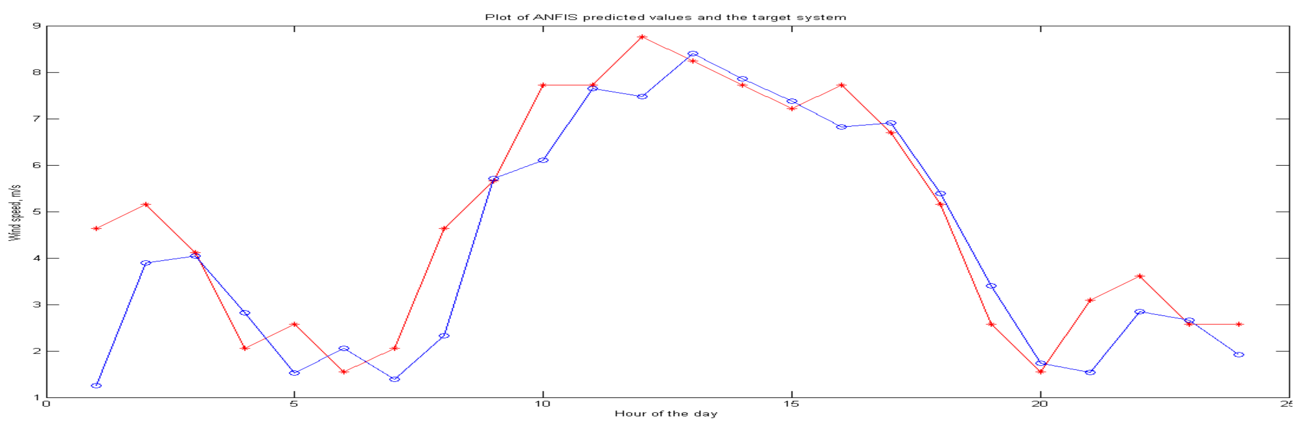
The 4 inputs, 2 bell-shaped membership functions per input univariate model generated by grid partitioning (A), 4 inputs, 2 bell-shaped membership functions per input multivariate model generated by grid partitioning (B), 6 inputs univariate model generated by subtractive clustering (C) and 6 inputs multivariate model generated by subtractive clustering (D) produced the best forecasting errors. The results are shown in table 1.

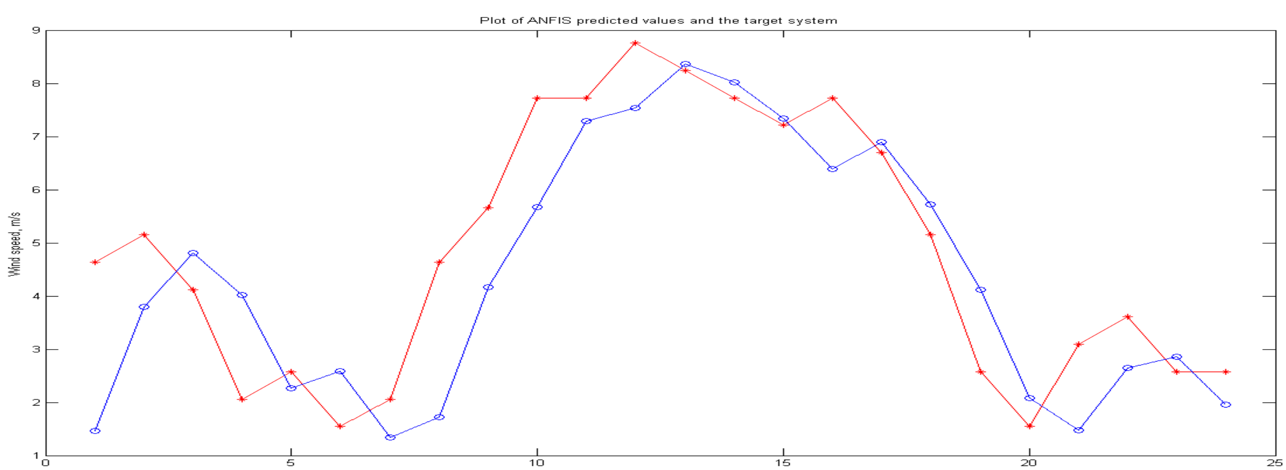
Table 1: MAE for the best ANFIS wind speed forecasting models

MODELS	**MAE**		
	TRAINING	**CHECKING**	**TEST**
A	0.8728	0.8710	0.8336
B	0.7117	0.6992	0.6545
C	0.8600	0.8564	0.8163
D	0.7296	0.7164	0.6555

One test case that was used to assess the models' performance was their response to diurnal variations in the wind speed. Diurnal variation is the change in the wind speed between the day and night time. In many locations the wind speed tends to be greater during the day than at night times. This poses an advantage to wind electricity operators as more energy is required during the day than at night. From tests carried out, the models were capable of predicting no or low wind speeds especially at times where there were long periods of very little or no wind.







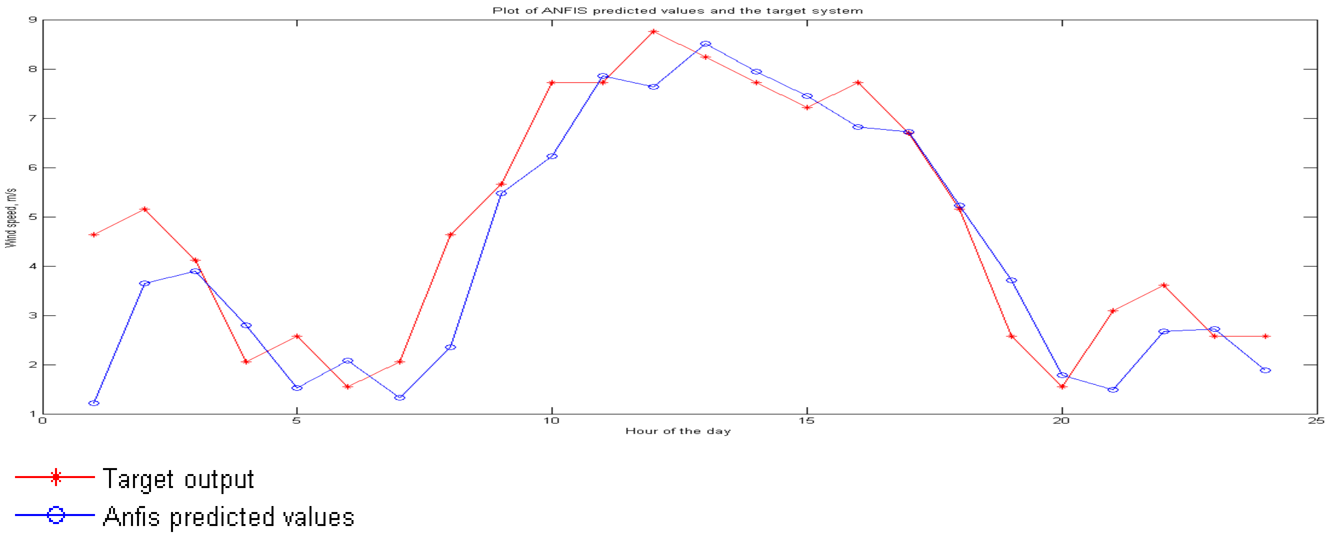


Figure 3: Plots of ANFIS predicted and target wind speed, m/s against Hours for a randomly selected day in Trinidad for models A, B, C and D respectively (from top to bottom)

When the wind speed either suddenly increases or decreases as seen when nights turn into mornings or when evenings turn into nights respectively, models A and C did not do very well in quickly picking up on these trends. However, when models B and D were tested, they did much better in this regard and therefore, the multivariate models using wind speed and air temperature as inputs provided better prediction results. From the short period of time tested, it can be seen from the plots in Figure 4 that the models imitated the general trend in the wind speed system; however there was a noticeable delay in the ANFIS predicted output and the target wind speeds. When these models were compared to models trained on fewer years of data, the discrepancy between the ANFIS predicted output and the target wind speed was far smaller with these models. In fact the other models' output did not follow the trend in the target wind speed system as well as Models A, B, C and D. Therefore, this delay seen in Figure 4 could be credited to the need for more than 10 years of training data. Also, from the results obtained in this study, it was observed that the most impact on the improvement of the performance of the models occurred when there was a change in the types of input data used. This illustrates that once a strong correlation between wind speed and other variables (such as relative humidity and rainfall) can be established, these variables can be used along with wind speed as inputs into the ANFIS models in order to help in the prediction of wind speed.

6 CONCLUSION

In order to increase the penetration of wind generators to the electrical grid, proper management of the dispatch of the electrical system must be acquired. In order for this to occur, it is important to have reliable and accurate techniques to forecast the wind speed in the very short term. One such technique is the use of ANFIS to develop wind speed forecasting models. The approach that was taken in this development was one proposed by J.S.R. Jang called System Identification. This is closer to a trial and error process that involved training different models and comparing them until a model that produced satisfactory results was obtained. Univariate and multivariate models were developed. 4 models that gave predictions with errors in the range of 25.5% and

32.5% were obtained. When the output of these models was compared to the actual data, the results proved to be very good.

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