Available online at www.sciencedirect.com

ScienceDirect

IFAC PapersOnLine 51-28 (2018) 414–419

Wind Power Forecasting

Q. Chen*, K. A. Folly**

** Electrical Engineering Department, University of Cape Town, Cape Town, South Africa, (e-mail: chnqin002@myuct.ac.za)*
*** Electrical Engineering Department, University of Cape Town, Cape Town, South Africa, (Tel: 0216504490; e-mail: komla.folly@uct.ac.za)*

Abstract: Accurate short-term wind power forecast is very important for reliable and efficient operation of power systems with high wind power penetration. There are many conventional and artificial intelligence methods that have been developed to achieve accurate wind power forecasting. Time-series based algorithms are known to be simple, robust, and have been used in the past for forecasting with some level of success. Recently some researchers have advocated for artificial-intelligence based methods such as Artificial Neural Networks (ANNs), Fuzzy Logic, etc., for forecasting because of their flexibility. This paper presents a comparison of conventional and two artificial intelligence methods for wind power forecasting. The conventional method discussed in this paper is the Autoregressive Moving Average (ARMA) which is one of the most robust and simple time-series methods. The artificial intelligence methods are Artificial Neural Networks (ANNs) and Adaptive Neuro-fuzzy Inference Systems (ANFIS). Simulation results for very-short-term and short-term forecasting show that ANNs and ANFIS are suitable for the very-short-term (10 minutes ahead) wind speed and power forecasting, and the ARMA is suitable for the short-term (1 hour ahead) wind speed and power forecasting.

Keywords: Wind power forecasting, artificial neural networks, ARMA, ANFIS.

1. INTRODUCTION

With the depletion of conventional energy resources and the deterioration of the environment, renewable energy will gradually become a crucial energy source (Ma, et al., 2009). Wind energy is one of the most available, affordable, and efficient energy sources. Despite this, wind speed varies from time to time and; it is difficult to accurately predict wind power (Wu & Hong, 2007).

There are many methods that have been developed to handle wind speed prediction. The conventional method presented in this paper is the time series autoregressive moving average (ARMA). In an ARMA model, the future value of a variable is assumed to be equal to a linear function of some past observations and random errors (Zhang, 2003).

The artificial intelligent methods that are discussed are Artificial Neural Networks (ANNs) and the Adaptive-network-based Fuzzy Inference System (ANFIS). An ANN is able to perform a nonlinear mapping between a set of input and output variables. An ANFIS is a fuzzy system whose parameters of the membership function have been adjusted by using neuro-adaptive learning methods like the techniques used for training neural networks (*Adaptive neural-fuzzy modeling*, 2017).

In this paper, the Autoregressive Moving Average (ARMA) is compared with artificial intelligence methods such as Artificial Neural Networks (ANNs) and Adaptive Neuro-fuzzy Inference Systems (ANFIS). Simulation results show that ARMA and the two artificial methods (ANNs and ANFIS) are suitable for the very-short-term (10 minutes ahead) and short-term (1 hour ahead) wind power forecasting.

The paper is organized as follows: The next section discusses the time-scale classification and wind power forecasting. Section 3 and 4 reviewed the Autoregressive Moving Average (ARMA) method and the artificial intelligence methods, respectively. Section 5 is concerned with data collection and analysis. Section 6 presents the simulation results and detailed discussions. Conclusion is given in Section 7.

2. TIME-SCALE CLASSIFICATION AND WIND POWER FORECASTING

2.1 Time-scale Classification

Different authors have different opinions about the time-scale classification of the operation of electricity systems. (Soman, et al., 2010; Wu & Hong, 2007; Zhang, 2003; Zhao, et al., 2011) separate the time-scale for the operation of electricity systems into four categories. Table 1 shows a summary of the time-scale classification for different forecasting techniques (Soman, et al., 2010; Wu & Hong, 2007; Zhang, 2003; Zhao, et al., 2011).

10.1016/j.ifacol.2018.11.738

Table 1. Time-horizon classification for wind power forecasting.

Time Horizon	Range	Applications
Very-short-term (in minutes)	Few seconds to 30 minutes ahead	-Electricity market clearing -Real-time grid operations -Regulation actions
Short-term (in hours)	30 minutes to 6 hours ahead	-Economic load dispatch planning -Load increment/decrement decisions
Medium-term (in days)	6 hours to 1 day ahead	-Generator online/offline decisions -Operational security in electricity market -Reserve requirement decisions
Long-term (in years)	Multiple-days-ahead to 1 year or more a head	-Maintenance planning -Operation management -Optimal operating cost -Unit commitment decisions - The feasibility study for design of the wind farm

The very-short-term and short-term time horizons are the main focus of this paper, as they are suitable for the real-time grid operations and load increment/decrement decisions.

2.2 Wind Speed Versus Wind Power

The output power of a wind turbine depends on the wind speed, which varies over a wide range of time and depends on regional landscape type, weather patterns, and seasonal variations (Wu & Hong, 2007) (Soman, et al., 2010).

The available and realistic wind power moving across the rotor blades per unit sweep area are defined as (1) and (2), respectively (Olaofe, 2013):

$$P_{av}(v) = \frac{1}{2}\rho(t)Av^3 \quad (1)$$

$$P_{real}(v) = \frac{1}{2}\rho(t)Av^3C_p(v) \quad (2)$$

where $P_{av}(v)$ is the ideal available wind power and $P_{real}(v)$ stands for the realistic power generated by the wind turbine in Watts(W), $\rho(t)$ is time varying air density, which depends on surrounding atmospheric pressure and temperature. A is the sweep area of the blades in (m^2), and v is wind speed (m/s). The ideal available wind power ($P_{av}(v)$) is related to the power $P_{real}(v)$ that can be generated by a wind turbine by means of the power coefficient (C_p). The C_p for a particular turbine is determined by the tip angle, the blade design and the relationship between wind speed and rotor speed. The maximum power coefficient (Betz limit) is 0.593 (Carrillo, et al., 2013). However, this value is not achievable in practice. The power coefficient at various operating conditions were not available. For the purpose of comparison, 0.5 was used as the power coefficient for all three models.

As indicated in (1) and (2), the air density is one of the very important factors affecting the amount of wind power generated by the wind turbine. The relationship between the air density, temperature and barometric pressure measured at the site is given by (3) (Olaofe, 2013).

$$\rho(t) = \left(\frac{P}{RT}\right)e^{-\left(\frac{gh}{RT}\right)} \quad (3)$$

where $\rho(t)$ is the time varying air density in (kg/m^3), P is barometric pressure in (Pa), T is the air temperature in (K), R is the specific gas constant for dry air, 287.058 (J/(kg.K)), g is the gravity of Earth, 9.81(m/s^2), h is the hub height above ground level in (m) (Olaofe, 2013).

2.3 Performance Measurements

It is difficult to accurately measure the performance of different wind speed and power forecasting models by comparing the forecasted wind speed plots against the actual wind speed plots. In this paper, the predictive performance was quantified by using the mean absolute error (MAE) and the root mean square (RMSE). The RMSE and MAE are defined as in (4) and (5), respectively (Mbuvha, 2017):

$$RMSE = \sqrt{\frac{1}{N}\sum_{h=1}^{N}(v_h - v_h^{forecast})^2} \quad (4)$$

$$\text{MAE} = \frac{1}{N}\sum_{h=1}^{N}|v_h - v_h^{forecast}| \quad (5)$$

where $v_h^{forecast}$ and v_h are the forecast and actual wind speed at time h, respectively; N is the number of forecast samples.
This model can also be used to measure the performance of the wind power forecasting models. In this case "v" will be replaced by "P" to denote power.

Small RMSE and MAE errors means that the difference between forecast wind speed/power and the actual wind speed/power is small. If RMSE and MAE are small enough, then the forecasting models will be deemed adequate.

2.4 Power Law Equation

The wind speed data provided by the Wind Atlas of South Africa were measured at maximum 62 m above ground which is lower than the minimum hub height of 80m for Vestas V90/1800 wind turbine which was selected for this study. As a result, the power law equation was used to estimate the wind speed at the desired hub height by using the wind speed measured at the lower height as inputs. Power law equation is given as (Joustra, 2014):

$$(v_1) = (v_0)\left(\frac{h_1}{h_0}\right)^{\alpha} \quad (6)$$

where v_1 is the wind speed measured at h_1 meters above ground and v_0 is the wind speed measured at h_0 meters above ground. In this paper, h_1 = 90 m and h_0 = 62 m. The representative surface roughness exponent (α) at a specific site is dependent on the terrain condition. The roughness exponent value of 0.089 was obtained by using (6) (Kwon, 2010).

3. AUTOREGRESSIVE MOVING AVERAGE (ARMA)

Many existing time-series methods can be used to forecast wind speed and power. The ARMA is one of the most robust and simple time-series methods. As a result, the ARMA method was used in this paper. The ARMA model consists of two components, namely, autoregressive (AR) and moving average (MA). In an AR model, a variable value in one period is related to its values in the previous periods. In a MA model, the possibility of a relationship between a variable and the residuals from previous periods is accounted for. Integrated term (I) in an ARIMA model is used when a variable y_t is not stationary. The wind data used in this paper is stationary. Therefore, integrated term was not required. ARIMA models without integrated term is ARMA.

ARMA (*p, q*) denotes an ARMA model with p autoregressive lags, q moving average lags. It can be defined as:

$$y_t = \sum_{i=1}^{p} \Phi_i y_{t-i} + \sum_{j=1}^{q} \theta_j e_{t-j} + \varepsilon_t \quad (7)$$

Where y_t is a variable at time t, Φ_i is the ith autoregressive parameter, θ_j the jth parameter of moving average, e_{t-j} is the lagged error term at time *t-j*, ε_t the error term at time *t*.

The Box-Jenkins methodology was used by (Burnham & Anderson, 2002) to fit an ARMA model to a set of wind speed data. In the first step, all the unusual observations were identified by plotting the wind speed data against time. Variances were stabilized in the second step by using a Box-Cox (*The Box-Cox transformation*, 2017). In the third step, the Dickey-Fuller test was carried out to test the stationarity of the wind speed data. Equation (8) was constructed to check the stationarity of the wind speed data.

$$\Delta y_t = (\rho - 1) y_{t-1} + e_t \quad (8)$$

Where ρ is coefficient of y_{t-1}, e_t is error term.
The model (8) is non-stationary, or a unit root is present if $|\rho| = 1$. The stationarity of the model with a drift and additional lags of the dependent variable can be tested by using an augmented Dickey-Fuller test. It is defined as:

$$\Delta y_t = \mu + (\rho - 1) y_{t-1} + \sum_{j=1}^{p-1} \theta_j \Delta y_{t-1} + \varepsilon_t \quad (9)$$

The next step is to use the autocorrelation function (ACF) and the partial autocorrelation function (PACF) to find a suitable ARMA model. The ACF is the proportion of the autocovariance of y_t and y_{t-1} to the variance of a dependent variable y_t as given in (10) (Katchova, 2017),

$$ACF(k) = \frac{Cov(y_t, y_{t-k})}{Var\ (y_t)} \quad (10)$$

where *Cov* stands for the covariance, and *Var* stands for the variance.

The partial autocorrelation function (PACF) was used to measure the degree of association between y_t and y_{t-k} when the effects of other time lags $y_{t-1}, \dots, y_{t-k-1}$ are removed.

Table 2. Properties of ACF and PACF.

	AR (*p*)	MA (*q*)	ARMA (*p, q*)
ACF	Tails off	Cuts off after lag *q*	Tails off
PACF	Cuts off after lag *p*	Tails off	Tails off

The properties of the ACF and PACF were used to determine the number of order of AR and MA (Katchova, 2017).

The next step is to find the preferred models based on the white noise test and goodness of fit. The final step was then to check if the residuals look like white noise by plotting the ACF of residuals. The 'forecast' package in R was used to model ARMA models. In this paper several models have been investigated and it was found that ARMA (2, 1) which consists of the 2nd order of the autoregressive and the 1st order of moving average has the best criteria test results. Therefore, it was used for the wind speed and power forecasting.

4. ARTIFICIAL INTELLIGENCE METHODS

4.1 Artificial Neural Network

ANNs can model complex non-linear relationships and approximate measurable functions to forecast wind speed and power. They are some of the most widely used models in the last decade for forecasting future events (Ma, et al., 2009) (Hippert, et al., 2001).

The key element of an ANN is the interconnected neurons. Each neuron or node works as an independent computation unit which is defined as (More & Deo, 2003):

$$Y = f[\sum(x_1 w_1 + x_2 w_2 + x_3 w_3 + \cdots) + \beta) \quad (11)$$

where x_1, x_2, x_3, ... are the input variables, such as wind speed, wind direction, temperature, etc; w_1, w_2, w_3, … are the connection weights; β is the bias value; *f* is the transfer function, which can be identity function or sigmoidal function.

There are many neural network architectures that have already been developed and implemented for forecasting applications. The ANN work-horse, the multilayer perceptron uses feed-forward architecture. The feed-forward multilayer network is a network in which no loop occurs in the network path (Aggarwal, et al., 2005). The structure of a feed-forward neural network with two input nodes, five hidden nodes, and on output node is shown in Fig. 1 (More & Deo, 2003).

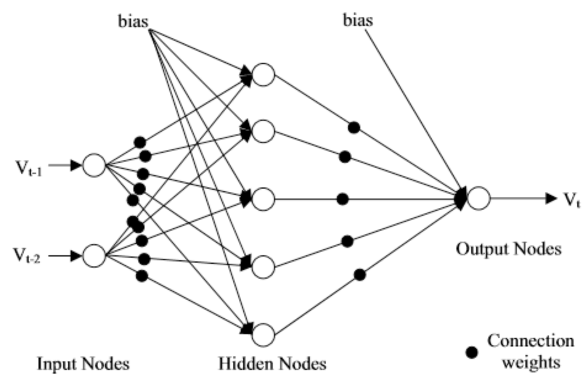

Fig. 1: Structure of a feed-forward neural network with two input nodes, five hidden nodes and one output node.

As can be seen in Fig. 1, there are two layers in the feed-forward neural network, namely, the hidden layer and output layer. The number of input nodes in the input layer is based on a prior knowledge of the behaviour of the system. Each input node represents an input variable which can be wind speed, wind direction or temperature and etc. It is harder to decide on the number of neurons in the hidden layer as compared to those of the input or output layers. (Hippert, et al., 2001) suggest using trial and error method to find a suitable number of neurons in the hidden layer. The number of output neurons required is dependent on the forecasting profiles.

There are three commonly used forecasting profiles, namely, iterative, multi-model and single-model. Iterative forecasting is done by forecasting a unit of wind data at a time. Multi-model forecasting is a common method for forecasting with regression; the number of models used depends on the gap between forecasting. The advantage of using multi-model forecasting is that each ANN is relatively small. Therefore, the overfitted is unlikely to happen. Single-model multivariable forecasting is done by using multiple variables as inputs to forecast multiple wind speeds as outputs at once (Hippert, et al., 2001). Single-model multivariable forecasting profile was used in this paper.

A training method was chosen for the neural network to fit the inputs and targets. Three commonly used training algorithms are Levenberg-Marquardt, Bayesian Regularization, and Scaled Conjugate Gradient. Levenberg-Marquardt requires more memory for computation but takes less time (Hagan & Menhaj, 1994). Bayesian Regularization usually requires more computation time, but it can result in good generalization for difficult, noisy or small datasets (Ticknor, 2013). Scaled Conjugate Gradient is suitable for large problems as it uses gradient calculations which require less memory (Saini & Soni, 2002) (Lazarevska, 2016).

In this paper, seven steps have been followed in the design process of the ANNs as discussed below.
Step 1: Collect, pre-process, and analyse wind data. The input to the model are the maximum, minimum and average wind speed measured at 62 m above ground.
Step 2. Create the network. The sigmoid function in the hidden layer was used to reduce the effect of extreme input values.
Step 3. Configure the network by dividing input vectors and target vectors into three sets, namely, training set, validation set, and testing set. 70% of data were used for training. Both validation and testing set used 15% of data. The best number of hidden neurons were selected by checking the performance of the model with different hidden neurons. 10 hidden neurons were used in this paper.
Step 4. Initialize the weights and biases for the network. The initial weight and biases were selected based on the relationship between the input and target data.
Step 5. Select Bayesian Regularization as the training algorithm, as it can result in good generalization for difficult, or small wind dataset.
Step 6. Validate the network.
Step 7. Use the network to forecast wind speed and power by importing the historical data into the input nodes.

4.2 Adaptive-network-based Fuzzy Inference System (ANFIS)

The adaptive neuro-fuzzy inference system (ANFIS) is a system with the combination of fuzzy logic technique and neuro network technique which bring the learning capabilities of the neural networks to fuzzy inference systems (MathWorks, 2017). In an ANFIS, the neuro-adaptive learning methods are used to adjust the parameters of the membership function. The shape of the membership functions is changing accordingly with the parameters. The structure of the neuro-fuzzy model for wind power forecasting can be presented as a special multilayer feedforward neural network.

Two commonly used fuzzy inference methods are Mamdani and Sugeno-type. In this paper, the Sugeno-type method is used in the ANFIS because it works well with adaptive techniques and optimization (*Sugeno-type fuzzy inference*, 2017). Therefore, the output membership functions are limited to constant and linear. The input to the model were maximum, minimum, and average wind speed measured at 62 m above ground.

The hybrid optimization method consisting of the backpropagation gradient descent and least-squares were used in this paper. The membership function used in this paper is Gaussian as it has similar shape as wind speed data. Training epochs and the training error tolerance needed to be specified once the optimization method is selected. The training process stopped when either training error tolerance or training epochs reached the predefined goals. The last step is to verify the performance of the model by using validation dataset and evaluation metrics (*Adaptive neural-fuzzy modeling*, 2017).

5. DATA COLLECTION AND ANALYSIS

The data used in this paper are collected from the Wind Atlas of South Africa. The data sets contain wind speed (m/s) measured at different heights, wind direction (°TN), temperature (°C), atmospheric pressure (hPa), and relative humidity (%) with 10 minutes resolution for the period from Midnight 31 December 2010 to Midnight 1 January 2017.

The data were analysed before applying them to the forecasting models as inputs. Descriptive statistics were used to summarize data from a sample using indices such as the mean, maximum, minimum and standard deviation. Inferential statistics were used to describe associations within the data by figuring out the correlation and regression (*Descriptive and inferential statistics*, 2017).

6. SIMULATION RESULTS AND DISCUSSION

6.1 Wind Power Forecasting

The forecast wind speeds were converted to the estimated wind speed at the hub height by using the power law equation (6). The estimated wind speeds at the hub height were then used to calculate the estimated wind power by using (2). Since there is no actual wind power data collected in this paper, the actual wind speed data were used to calculate the "calculated actual wind power". The plots of the calculated wind power and the very-short-term forecast wind power are shown in Fig. 2.

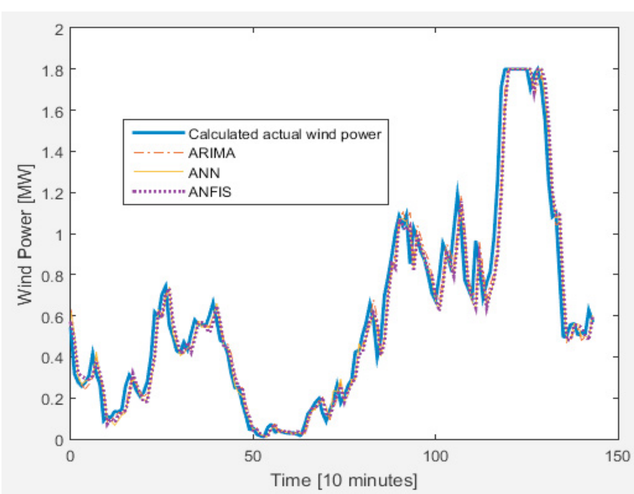

Fig. 2: Plots of the calculated actual wind power and the forecast wind power of the ARMA (2, 1), ANN and ANFIS over very-short-term (10 minutes ahead) time horizon.

As can be seen in Fig. 2, the plots of all three models track the plot of the calculated actual wind power closely. This agree with the result as suggested by (Chang, 2014) (Ma, et al., 2009).

Fig. 3 shows the plots of the calculated wind power, the forecasted wind power using ARMA, ANNs, and ANFIS for short-term time horizon.

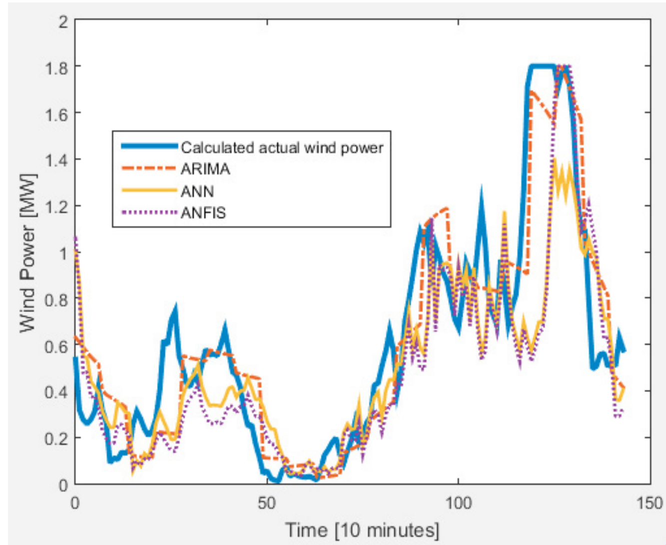

Fig. 3: Plots of the calculated actual wind power and the forecast wind power of the ARMA (2, 1), ANN and ANFIS over short-term (1 hour ahead) time horizon.

As can be seen in Fig. 3, the plot of forecast wind power (red dot-dash line) of the ARMA (2, 1) tracks the calculated actual wind power closely for the most of samples. The plots of ANN (orange solid line) and ANFIS (purple dot line) have similar shape. This is expected as both methods have good training ability. The margin between the forecast wind power of ANN and the calculated actual wind power (blue solid line) is small for the most of samples. However, the margin between samples 120 to samples 130 is big. This is due to the sharp increase of the calculated actual wind power. The ANN wasn't able to accurately forecast wind power when the difference between adjacent samples is big. The evaluation results will be much better if the margin between samples 120 to samples 130 is reduced. Table 2 quantifies the performance of each model.

Table 2: Summary of the normalized RMSE and MAE for wind power forecast.

Time Horizon	ARMA		Artificial Neural Network		ANFIS	
	RMSE [%]	MAE [%]	RMSE [%]	MAE [%]	RMSE [%]	MAE [%]
Very-short-term (10 minutes ahead)	5.8	4.2	5.6	3.8	5.7	3.9
Short-term (1 hour ahead)	11.3	8.8	18.1	12.3	18.4	12.2

As can be seen in Table 2, all three models perform well for the very-short-term time horizon wind power forecasting. For the short-term forecasting, the ARMA has the lowest forecasting errors among the three models. The evaluation results for very-short-term forecast are expected, as all three methods are very good at very-short-term wind power forecasting. However, the short-term forecast results of the ANN and ANFIS are not as good as one would have expected. It can be seen from table 2 that RMSE and MAE values increase with the forecasting time horizon. Therefore, we can conclude that the performances of all the models degrade with the increases of the prediction lead time.

7. CONCLUSIONS

Based on the evaluation results, the ARMA (2, 1) has the lowest wind power forecasting error over the short-term time horizon. It has 3.5% and 3.4% less MAE errors than the ANNs and ANFIS respectively. The difference among short-term wind power forecasting errors of three models is well within the errors commonly found in the collected data. Therefore, more data and simulations are required to make valid comparison. The performance of artificial intelligence methods, (ANNs and ANFIS) perform and the conventional method over the very-short-term time horizons is very similar. All three models have less than 6% very-short-term wind power forecasting errors.

The ANNs and ANFIS have similar performance results. According to the evaluation results, both artificial intelligence and conventional methods are suitable for the very-short-term and short-term wind power forecasting.

REFERENCES

Aggarwal, K., Singh, Y., Chandra, P. & Puri, M., (2005). Bayesian regularization in a neural network model to estimate lines of code using function points. *Journal of Computer Sciences,* 1(4), pp. 505-509.

Anon., n.d. *Adaptive neural-fuzzy modeling.* [Online] Available at:https://www.mathworks.com/help/fuzzy/adaptive-neuro-fuzzy-inference-systems.html [Accessed 23 October 2017].

Anon., n.d. *Descriptive and inferential statistics.* [Online] Available at: https://statistics.laerd.com/statistical-guides/descriptive-inferential-statistics.php [Accessed 28 October 2017].

Anon., n.d. *Sugeno-type fuzzy inference.* [Online] Available at: https://uomustansiriyah.edu.iq/media/lectures/5/5_2017_02_28!06_24_14_PM.pdf [Accessed 12 November 2017].

Anon., n.d. *The Box-Cox transformation and ARIMA model fitting.* [Online] Available at: http://www.personal.psu.edu/asb17/old/sta4853/files/sta4853-14print.pdf [Accessed 12 November 2017].

Beale, M. H., Hagan, M. T. & Demuth, H. B., (2017). *Neural network toolbox™ getting started guide.* Natick, MA: The MathWorks, Inc..

Burnham, K. P. & Anderson, D. R., (2002). *Model selection and multimodel inference: a practical information-theoretic approach, Second Edition.*Springer-Verlag, New York.

Carrillo, C., Obando Montano, A., Cidras, J. & Diaz-Dorado, E., (2013). Review of power curve modelling for wind turbines. *Renewable and Sustainable Energy Reviews,* Vol. 21, pp. 572-581.

Chang, W.-Y., (2014). A Literature Review of Wind Forecasting Methods. *Journal of Power and Energy Engineering ,* Vol. 2, pp. 161-168.

Hagan, M. T. & Menhaj, M. B., (1994). Training feedforward networks with the Marquardt Algorithm. *IEEE Transactions on Neural Networks,* 5(6), pp. 989-993.

Hippert, H. S., Pedreira, C. E. & Souza, R. C., (2001). Neural networks for short-term load forecasting: a review and evaluation. *IEEE Transactions on Power Systems,* 16(1), pp. 44-54.

Joustra, Y., (2014). *Forecasting of wind power production in the Netherlands,* Enschede, Netherlands: University of Twente.

Katchova, A., (2017). *Econometrics Academy.* [Online] Available at: https://sites.google.com/site/econometricsacademy/econometrics-models/time-series-arima-models [Accessed 31 October 2017].

Kwon, S.-D., (2010). Uncertainty analysis of wind energy potential assessment. *Applied Energy,* Vol. 87, pp. 856-865.

Lazarevska, E., (2016). *Comparison of different models for wind speed prediction.* Florence, Italy, s.n.

Ma, L. Luan, S. Jiang, C. Liu, H. Zhang, Y. (2009). A review on the forecasting of wind speed and generated power. *Renewable and Sustainable Energy Reviews,* Vol. 13, pp. 915-920.

MathWorks, T., (2017). *Fuzzy Logic Toolbox™ User's Guide.* Natick, MA: The MathWorks, Inc..

Mbuvha, R., (2017). *Bayesian neural networks for short term wind power forecasting.* Stockholm, Sweden: KTH Institute of Technology School of Computer Science and Communication.

More, A. & Deo, M., (2003). Forecasting wind with neural networks. *Marine Structures,* Vol. 16, pp. 35-49.

Olaofe, Z. O., (2013). *Wind energy generation and forecasts: a case study of Darling and Vredenburg sites. Msc Thesis* Cape Town: University of Cape Town.

Saini, L. M. & Soni, M. K., (2002). Artificial neural network-based peak load forecasting using conjugate gradient methods. *IEEE Transactions on Power Systems,* 17(3), pp. 907-912.

Soman, S. S., Zareipour, H., Malik, O. & Mandal, P., (2010). A review of wind power and wind speed forecasting methods with different time horizons. In: EEE, ed. *North American Power Symposium (NAPS).* s.l.:s.n., pp. 1-8.

Ticknor, J. L., (2013). A Bayesian regularized artificial neural network for stock market forecasting. *Expert Systems with Applications,* Vol. 40, pp. 5501-5506.

Wu, Y.-K. & Hong, J.-S., (2007). *A literature review of wind forecasting technology in the world.* IEEE, Lausanne, Switzerland.

Zhang, G. P., (2003). Time series forecasting using a hybrid ARIMA and neural network model. *Neurocomputing,* Vol. 50, pp. 159-175.