TIME SERIES WIND SPED PREDICTION WITH ENERGY MAPPING USING HYBRID INTRINSIC MODE FUNCTION (IMF) AND EXTENDED INPUT NEURAL NETWORK (EINN)

S. M. Lawan[1,2], W. A. W. Z. Abidin[2], T. Masri[2], F. A. Umari[1], A.Y. Abdullaahi[1]., S. J. Kawu[3]
[1]Department of Electrical Engineering, Kano University of Sci.& Tech. Kano, Nigeria.
[2]Department of Electrical and Electronics Engineering, Universiti Malaysia Sarawak,
[3]Department of Mechanical Engineering, Baze University Abuja-Nigeria.
[1]salisumuhdlawan@gmail.com* , [2] wzaazlan@unimas.my , [3] mthelaha@unimas.my
[4] faizaaliyu104@yahoo.com, [5] ayayusuf234@gmail.com , [6] jkawu75@yahoo.com

Keywords: –
Artificial Neural Network (ANN), Wind Speed, Intrinsic Mode Function (IMF) and Extended Input Neural Network (EINN), Sarawak

Article History: –
Received: May, 2019.
Reviewed: June, 2019
Accepted: August, 2019
Published: September, 2019

ABSTRACT

Accurate and precise wind speed predictions are a prerequisite requirement that is necessary before siting of wind turbines. The output power of wind energy system is completely depends on the behavior of wind speed; a small deviation of wind speed will lead to large energy losses. This paper presents a new technique for predicting the wind speed based on hybrid model Intrinsic Mode Function (IMF) and Extended Input Neural Network (EINN) in the regions where there are limited wind stations. In the first instant, the important parameters for training the artificial neural network (ANN) are acquired using the principal component correlation analysis and wind speed signal decomposition, these parameters used as inputs to the ENN. To illustrate the trend and seasonal factor in the wind speed time series, the data are decomposed into six empirical time series IMF, the nonlinear and non- stationary characteristic of wind speed is handled by empirical mode decomposition (EMD) and EINN respectively. The final predicted values are obtained by summing all the individual prediction sub models. Wind speed data observed in the existing wind stations in Sarawak for a period of 1 year from 2015 to 2016 were used for the simulation. The model implementation confirmed that the proposed model is robust and capable compared to auto-regression integrated moving average (ARIMA) method.

1. INTRODUCTION

The energy content in a wind is renewable, clean, inexhaustible and naturally abundant. It is also environmentally risk-free. The hydrocarbon based fuels are costly, in addition, they pollute lower layer of the atmosphere, and led to the emission of greenhouse gasses and raise the incidence of global warming. The application of wind energy results in savings of 0.5 to 1 tons of greenhouse effect gas [1]. In fact, this is the main goal set up by the Kyoto protocol to reduce the GHG by 5% of the 1990 levels within five years from 2008-2012 [1]. Wind power has been applied for over many decades for sailing ships, grinding grain, water pumping. In recent years, it has become an important source used for electrical power generation. Recently, more attention has been paid on wind power research and development, especially in terms of electrical energy production.

The scale-up development of wind power in the developed nations, such as Europe and in the United State of America with objective to lessen the environmental impacts of the conventional energy resources has motivated the developing countries also to set up a road map in line to implement their mission on renewable energy. The global annual and cumulative installed capacity of the wind energy power of the world from 2001 to 2016 rose exponentially from 6,500MW to 54,600MW and 23,900MW to 486,749MW respectively [2]. In Asia, China, India, Taiwan, South Korea and Pakistan are the leading countries with the total installed capacity of 168,690MW,28,700MW,3,234MW,682MW, 591MM and 56MW respectively [2]. The rest of the countries shared 276MW in which Malaysia is inclusive. This focuses the attention of Malaysia Government to bring in renewable energy in the fifth fuel diversification policy under vision 2020, and targeted 5% of the total country energy mix from renewable resources [3].

Wind speed is the most important parameter in wind energy evaluation; a small deviation in wind speed will lead to large error in the wind turbine output. Because of the aforementioned reasons, wind speed must be treated with high degree of precision [4].Wind data can be obtained via different sources such as existing literature, conducting experiments, and prediction models [4]-[5]. Wind speed prediction is being topic of interest by many researchers, because it has been proved to give a close estimate with the measured wind speed. Wind speed prediction can be performed using statistical methods, mathematical models, and nowadays is become popular to use machine learning to estimate the wind speed. [6]. It has been shown that there is no mathematical model either physical or statistical model will give a precise model of wind speed, due to ill-defined nature of wind speed, a such the application of machine learning and deep learning is more acceptable in developing a prediction model [7, 8].

Motivated by the above discussions, this paper aims to predict the wind speed values and also develop a wind resource map for Sarawak based on available wind station data and hybrid soft computing model. The remainder of the paper is organized as follows: section 2 presents and overview of wind speed prediction, proposed methods are presented in section 3, follow by results and discussion in section 4, while section 5 concludes the paper..

2. WIND SPEED PREDICTION: OVERVIEW

Prediction techniques are widely applied in engineering and econometric applications. A lot of approaches on prediction have been implemented and presented in scientific literatures. Predicting outcomes in decision making conducted [9]. Electrical power load prediction model performed in [10]. Performance prediction for local grid scheduling [11]. Many types of solar irradiance prediction models have been developed and utilized [12].Wind speed prediction is more tedious compared to other prediction techniques like solar, electrical load and local grid scheduling, due to complexity and stochastic nature of wind speed. The predictions methods can be catalogued into two different groups depend upon the type of algorithm used. The first group is based Numeric Weather Prediction (NWP) and the second group covers, among others, Artificial Intelligence (AI) fuzzy logic control, ANN and statistical modeling [13]. An extensive review on wind speed prediction with different time horizons can be found in [14, 15].

2.1 Short-term wind speed prediction

Nowadays, short time wind speed prediction has been given considerable attention. Short-term wind speed prediction with the ANN model has been used in Batman, Turkey, [16] weather data has been modeled to predict wind speed by using feed forward with back propagation algorithm, the predicted wind speed differ by maximum 5% from the actual values. In a similar study, [17] reported an effort for short-term wind prediction based on time series weather data using an improved ANN. ANN has also used for wind speed parameter estimates between cities in Turkey [18]. Based on three layers ANN Lee et al. [19] developed and evaluated a wind speed model for Jeju. Detail analysis for implementing short-term wind speed using ANN has been systematically discussed in [20].

According to [21] have developed architecture for estimating short term wind speed by using linear machine classifier and a set of k multiplier perceptron. The results obtained showed that the proposed hybrid model improves the accuracy compared to MLP alone. Predicted wind speeds obtained from meteorological stations are used for short term prediction based on Radial Basis Function Network and Kernel Machines [22]. Test results of the study indicate that Kernel machines present series of advantages to create wind speed prediction. Evolutionary product unit neural network (EPUNN) proposed for short-term prediction, this novel hybrid approach has been proved to perform better and provide a precise wind speed prediction compared to traditional neural network. Likewise, [23] introduced in the input data using banks of artificial neural network, the method improves the system performance compared to the one obtained using single a NN. Another three different improved ANN method developed in [17]. The network models were created by customizing the object properties, the models were validated using actual wind speed data. The simulated results show a significant improvement of the network prediction accuracy. ANN with Markov chain proposed in [24]. This integrated approach was found to be effective for predicting short-term wind speed, and also the results are modified for long term patterns due to stimulation of the Markov chain.

Five different mining algorithms have been used to test wind speed datasets [25], support vector machine (SVM) regression algorithm and multilayer perceptron (MLP) performed excellently in predicting short-term wind speed. Wavelet and Particle Swarm Optimization (PSO) integrated approach was used to predict short-time wind speed in [26]. Chaotic time series analysis and SVM regression have been presented in [27]. The RMSE of testing data, obtained by the SVR is 0.069 while it is 0.101 offered by the ANN with 8 inputs respectively. Probabilistic method for wind speed prediction based on ensembles and Bayesian Modeling Averaging (BMA) were presented in [28]. This method provides quick and standardized probabilistic prediction compared with other numerous formulations. A combination of radial basis function neural network (RBFNN) and fuzzy logic techniques are applied for a wind speed estimation in [29], the test result shows that it can be used effectively for predicting short time wind speed. Wind speed prediction based on spatial correlation [30], and a hybrid fuzzy model for wind speed using spatial correlation [31].

2.2 Long-term wind speed prediction

Long term wind speed is a vital tool for maintenance scheduling to obtain an optimal operating cost, and also it allows understanding the detail knowledge of wind speed characteristics in a target area. Many approaches have been proposed and presented in Scientific literature, such as: Recurrent neural network (RNN) [32], first definite seasonal index method and the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) proposed in [33], the predicted errors were compared to the ones achieved from GARCH, ARMA and support vector machine (SVM). The developed hybrid system is efficient and simple for predicting average daily hour wind speed. Measure-Correlate-Predict (MCP) techniques were reported in [34]. An improved MCP method that integrated ANN has been presented by [35]. Detailed reviews on wind speed prediction using reduced SVMs with feature selection and ANNs for Wind Speed Forecasting can be found in [36- 37].

The accuracy of the persistence method drops significantly with increase in prediction time horizons, the Kalman filter is fairly tedious to estimate the parameters, and besides it presumes that the statistical properties of noise are identified. Mother wavelet needs much trial and error procedures. The learning rate of ANN alone is slow and is very simple to descend into locally optimal solution. Spatial method is totally depending on the spatial correlation curves between the study areas wind speeds, and also it is hard to observe the data in applications. SVM algorithms require a series of mathematical transformations for instance, formulation and translations of a real problem in convex programming and generate solutions via convex optimization, which is also tedious and time consuming.

The most relevant studies conducted in the area are the work of [38].The key part of the method is the ‘empirical mode decomposition’ method with which any complicated data set can be decomposed into a finite and often small number of ‘intrinsic mode functions’ that admit well-behaved Hilbert transforms. [38]. A new Ensemble Empirical Mode Decomposition (EEMD) is presented in [39]. This new approach consists of sifting an ensemble of white noise-added signal (data) and treats the mean as the final true result. Finite, not infinitesimal, amplitude white noise is necessary to force the ensemble to exhaust all possible solutions in the sifting process. In this work of [40] an algorithm based on the ensemble empirical mode decomposition (EEMD) is presented. The key idea on the EEMD relies on averaging the modes obtained by EMD applied to several realizations of Gaussian white noise added to the original signal. Two hybrid models, self-adaptive time-frequency methodology, ensemble empirical mode decomposition (EEMD) coupled with support vector machine (EEMD-SVM) and EEMD model tree (EEMD-MT), were employed to forecast monthly wind speed [40].

Prior to machine learning, wind speed prediction was carried out using boundary layer flow, a mass-consistent model, AIOLOS, a mass-consistent code, Analysis of airflow to generate the wind field over complex terrain conditions based on GIS. The kinematics approaches tend to be complex and inefficient in terms of practical situations. When it comes to estimating wind speed over a given area, no mathematical model (either physical or numeric) provides a perfect, definitive solution. Based on the aforementioned reasons, soft computing models like, ANN, SVM and SA are found to be more acceptable [7-8].

The NN prediction models provide the most effective capability for wind speed forecasting. Using these NN models, the lowest RMSE, significantly less processing time, and accuracy and reliability are attained, showing that these models are much better than other prediction models. ANN understands the data, simulates wind speed in advance based on training, and predicts wind speed with the highest accuracy. Simulation outcomes demonstrate that the predicted wind speed is in good agreement with experimental measured values. Simulation using an ANN model shows that wind speed can be predicted with or without monitoring, provided that there is a reference wind station in the area.. It is clear that from the above review, NNs are robust and promising in terms of wind speed prediction. In the listed studies, the NN model has a non-topographic approach. Surface roughness parameter and terrain elevation influence the wind flow from one location to another. Hence, in this study, an input extended NN, EMD and MCP methods is suggested, for long-term wind speed, in non-monitored locations.

From the review hereof in section 2, it is clear that selecting appropriate wind speed prediction model is very important. In this paper, a hybrid methodology for wind speed prediction and decompose predicted wind speed (ANN+IMF) is proposed. The main idea behind this is to generate small wind speeds after it has been predicted, also to decompose observed wind speed so as to generate a harmonized wind speed database that could be feed into the MCP equation efficiently. The proposed improved methodology in this paper comprises of the application of multiple wind stations, spearman rank correlation is used to test and select the best strength wind speeds, and then, the time series wind speed was decomposed into a finite number of empirical modes known called IMF and feed into the neural network for the implementation purposes

3. PROPOSED SIMPLIFIED SOLUTIONS

3.1 Correlation Coefficient Estimation

This research also investigates the benefits of selecting the suitable reference point site for the correlation technique. There was a significant variation in the simulation results when the wind speed of one site was applied to simulate the wind speed of the other and vice versa, for the same event. An additional important factor in this study would be the fact that most of the preferred areas do not possess a consistent topographic morphology in-between, something that tends to make the wind speed correlation procedure more complicated. A Spearman's rank correlation has been adopted here, in particular x_1, x_2, x_3 $x_4, \ldots\ldots, x_i$ and $y_1, y_2, y_3, y_4, \ldots., y_i$ are two sets of wind speed data. Since wind speed is nonlinear, a Pearson type can be computed in the rank of x and y values using:

$$R_{ho} = \frac{\left[1 - 6\sum (d_i)^2\right]}{\left[n(n^2 - 1)\right]} \qquad (1)$$

where d is the difference between the rank of $_{xi}$ and $_{yi}$ and r_s is +1 if there is perfect agreement between the two sets of rank or *-1* if there is complete disagreement between them

3.2 Decomposition of wind speed values

EMD is a new data driven techniques introduced by [38-39] and uses to decompose a non-stationary and non-linear signal into the IMF. Recently, EMD has received considerable attention in terms of application and interpretations. The merit of EMD is that, the basic functions are derived from the signal itself. In this paper the wind speed signal w(t) is decomposed into using Equation 2:

$$w(t) = \sum_{j=1}^{K} IMF_j(t) + r_k(t) \qquad (2)$$

w(t) is the wind speed and $r_k(t)$; indicates the signal residue.

3.3 Artificial Neural Network (ANN) Modeling

ANN is a powerful tool of modeling time series data without any mathematical formulations. A feed forward NN back propagation based was built because already the wind speeds have been decomposed into the IMF, the network consisted of three layers: input layer; hidden layer and output layer as shown in the ANN structure in Figure 1 was designed using Easy-NN plus commercial neural network software. Prior to the simulation all the data has been preprocessed and normalized in the range of [-1, 1] and then arranged into seventy percent for training, twenty percent for testing and ten percent for validation. Levenberg-Marquardt learning algorithm was used to train the network to reduce delays for the selected network.

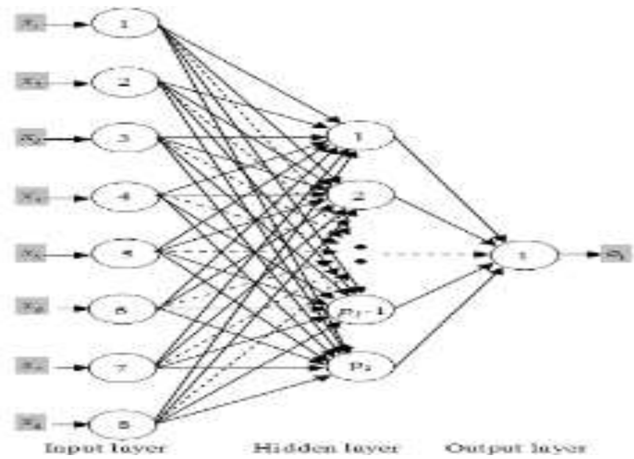


Fig. 1. ANN Model

where: X_1: Latitude, X_2: Longitude, X_3: Altitude, X_4: Terrain elevation, X_5: Month, X_6: Temperature, X_7: Atmospheric pressure, X_8: Relative humidity and O_i: Wind speed.

Once the training is completed Equations used to judge the suitability of the models:

$$R = \frac{\sum_{i=1}^{N}(t_i - \bar{t}) * (o_i - \bar{o})}{\sqrt{\sum_{i=1}^{N}\left(t_i - \bar{t}\right)^2} * \sqrt{\sum_{i=1}^{N}(o_i - \bar{o})^2}} \qquad (3)$$

$$MAPE = \left[\frac{1}{N}\sum_{i=1}^{N}\left|\frac{t_i - o_i}{t_i}\right|\right] * 100 \qquad (4)$$

N represents the number of data points, and t_i, o_i stands for target (reference) value and the model predicted value for data point i. Bars indicate average values.

3.4 Measure–Correlate-Predict (MCP)

Measure–correlate–predict (MCP) algorithms are applied to forecast the wind resource at target sites for wind power development. MCP approaches model the relationship between wind data (speed or direction) measured at the target site, commonly over a length of up to a year, and concurrent data at a close by reference site. The model is then utilized with long-term data from the reference site to predict the long-term wind speed distributions at the aim for site. In this study, due to time and cost implication, the short-term wind speed was predicted based on a hybrid model. Then, using Equation 5, two stations in planar regression has been modeled to predict the long wind speed values.

$$\bar{y} = mx + nz + b \qquad (5)$$

where $\bar{y}$ is the predicted wind speed at the target site, x is the observed wind speed at the reference site 1, z is the observed wind speed at the reference site 2, $\boldsymbol{m}$, $\boldsymbol{n}$ and b are the slope and offset determined from linear regression Equation 5 was solve using Maple-Soft Software,. Variances and covariance's were calculated from the linear regression to determine confidence intervals for the predicted mean wind speed assuming that the assumptions of the linear regression approach is applied.

3.5 Algorithm Applied

The methodology has been adopted from the research work conducted in [23] with modifications. The work of [23] used $\boldsymbol{y=mx+c}$, where y is the predicted wind speed at the target site, x is the observed wind speed at the reference site, m and b are the slope and offset determined from linear regression. The series stages follow are; data pre-screening, treatment of nonlinear non-stationary behavior of wind speed, back propagation NN and MCP. Summary of the ANN prediction, EMD and MCP topology was shown in Figure 2. Data pre-screening was carried out in order to generate an error free database, before the data was inserted to the NN. All the data available at reference station were stored in a database. The target area where there is limited or no wind station, a prediction model was developed. The model was developed using FFNN, trained with LM algorithm. The model was trained, tested and validated before it was implemented in the target areas. The observed and predicted wind speeds were later subjected to EMD in order to generate wind speed wind lesson-stationary and non-linear characteristics. The EMD wind speed data were stored and feed-in to the MCP model for long term wind speed prediction.

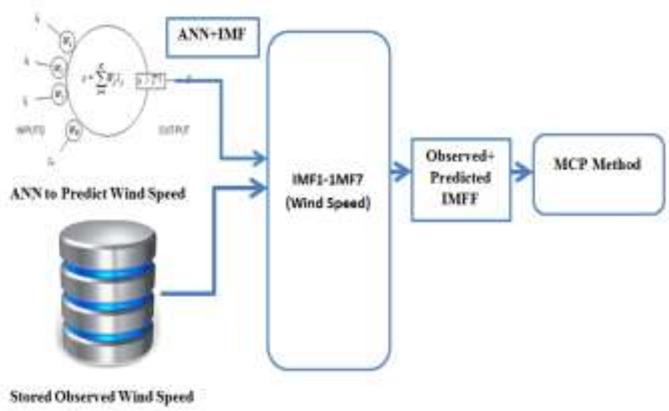


Fig. 2. Summary of the ANN prediction, EMD and MCP Methodology

3.6 Estimation of Wind Power Density and Energy Map Development

The mechanical wind power can be obtained using:

$$P = \frac{1}{2}\rho A V^3 \qquad (6)$$

where ρ is the air density, A is swept area, and v is the wind speed, wind power density indicates the potential per unit area, in order to compute the exact potential, the summation of data taken or predicted over a time interval was performed using Equation 7.

$$WPD = \frac{1}{2}\left(\frac{1}{n}\right)\sum_{i=1}^{n}\rho_i \, v_i^3 \qquad (7)$$

where n is the number of wind speed readings ρ_i is the i_{th} readings of air density and v_i is the i_{th} readings of wind speed.

The existing and predicted wind speeds were used in the establishment of annual wind energy map for the geographic locations using Geographical Information System (GIS). The wind energy mapping was plotted using ARCGIS 9.3 software. The coordinates of each study area were converted into degree decimal units. The world geodetic system of 1984 was used to generate the coordination system, and was used to create the contour lines. Kriging geo-statistical interpolation was applied to develop the isovent maps.

4. RESULTS AND DISCUSSION

This paper integrates the use of daily average hourly wind speeds observed at various stations in Sarawak, and predicts the hourly wind speed by using a hybrid (IMF+ENN) models. A set of one year data from January to December, 2016 is employed in the studies.

4.1 Correlation outcomes of the station used

Correlation coefficients for the stations under considerations were analyzed using self-developed application using MS Excel 2010 packages. The result of correlation matrix shows that there is a good correlation between Kuching and Bintulu (0.78), Kuching and Kapit (0.89), Bintulu and Miri (0.92), Kapit and Limbang (0.67). It is clear from the quantitative values obtained, the values varied in the order of lowest to highest is 0.67-0.92. A minimum and maximum value of 0.56-0.89 has been reported in [26]. The results have been accepted since the tabulated runs at 5% level of significance.

4.2 Results of decomposed wind speed

The hourly wind speed data (Figure 3) of wind station located in Sri Aman Sarawak are employed to evaluate the proposed hybrid model. Total 2500 samples are taken, out of these, 4000 data are used for training and rest used for testing. Firstly, the wind speed data were

decomposed into subseries using EMD technique. The decomposed series is shown in Figure 4. The observed and predicted wind speed was decomposed using IMF. Before, decomposition take place, all the wind speed values was scaled to -500 to 500 in order to clearly see the values in y axis after EMD is done. The decomposed wind speed based on the IMF was performed as stated in the methodology section.

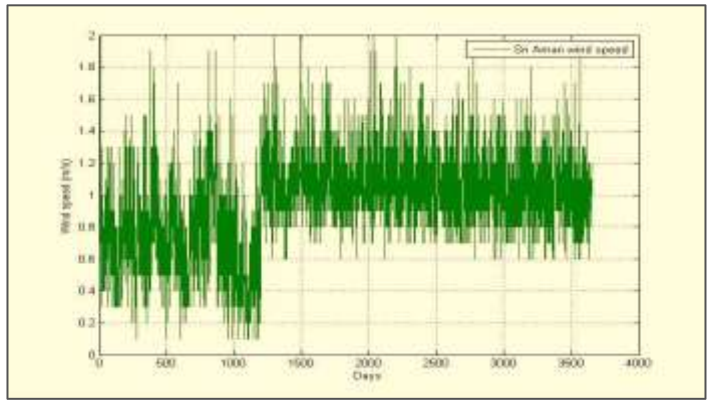


Fig. 3. Original wind speed data of Sri Aman for 10 years

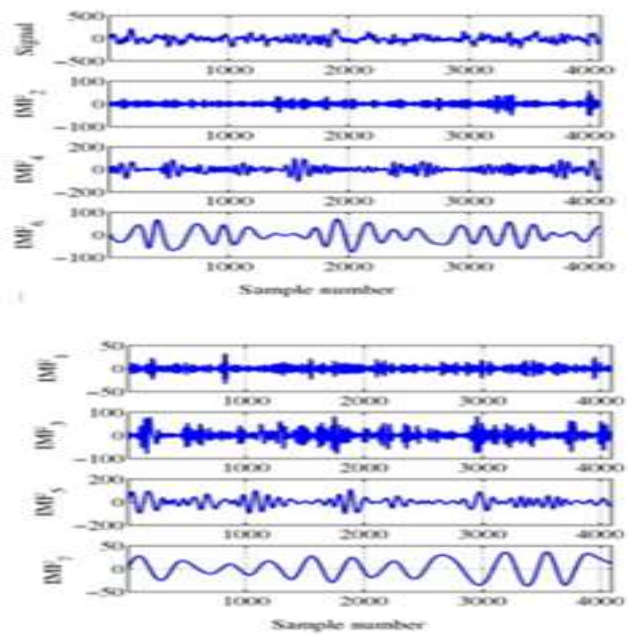


Fig 4.: IMF_1-1MF7+ Residual

Figure 4 shows the seven IMF functions including one residual function, it is clear that the wind speed is non-stationary, even though, the wind speed is positive IMF1 shows a high oscillation with high frequencies, while IMF_2-IMF_7 vary slowly and symmetrically. It can be seen that in Figure 4, the nonlinearity properties of wind speed reduces from original signal as IMF increased, at IMF_6 and IMF_7 the wind speed on linearity is reduced. The IMF wind speed was **later** used during the model implementation.

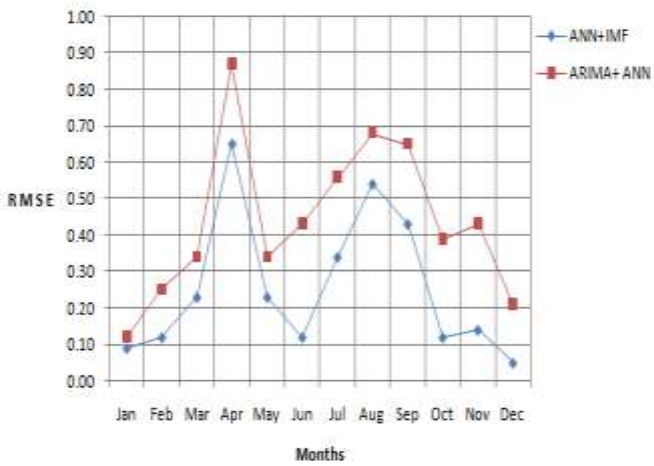


Fig.5. Wind speed error analysis between *IMF+ANN and ARIMA+ANN*

4.3 Predicted Results of the Developed ANN and the MCP methods

The training of neural networks is performed, the network performances were judged in terms of Mean Absolute percentage Error (MAPE) and Mean Square Error (MSE) whose equation are provided in section 3.5. Based on the training data sets, the MAPE and MSE varied from 0.00123-1.899 and 1.2-17.7% respectively. Figure 5 shows the error analysis carried out in order to judge the performance of the purpose method with conventional techniques. The purpose of doing this is to check how cable the proposed method could be applied. The RMSE was plotted against monthly wind speed. The minimum and maximum errors of ANN+ IMF were almost close to 0.05 and 0.65. While in the ARIMA+ANN the minimum and maximum RMSE are 0.10 and 0.85 respectively. The results proved the superiority of using ANN+IMF over ARIMA+ANN.

In Figure 6, results comparison was made between real and predicted monthly wind speed data. The brown color shows the predicted data based on the developed model, while, blue color donates the real wind speed data measured in the wind station. In all he months of year, the predicted and observed data showed a good correlation.

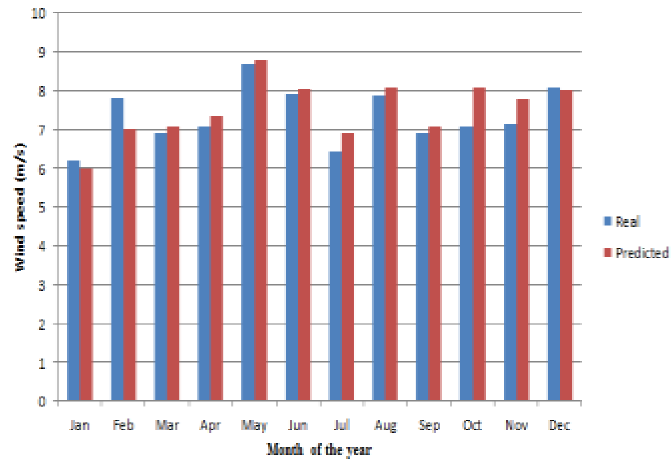
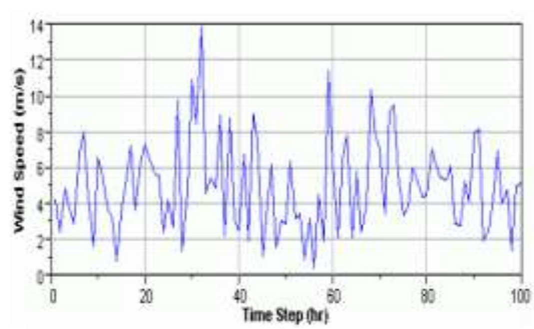
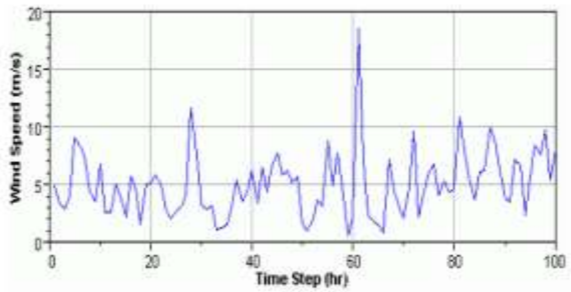


Fig. 6. Actual and predicted wind speed

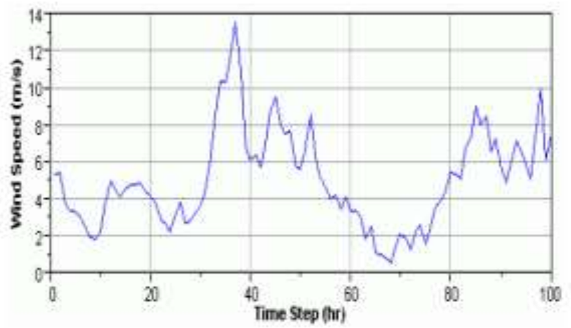
Wind speed time-series data typically exhibit autocorrelation, which can be defined as the degree of dependence on preceding values. The effect of autocorrelation using sample data of 100 is shown in Figure 7 below. In the absence of autocorrelation, each data point is completely independent of the previous values and the data points jump up and down at random, as shown in part a) of Figure 7. In a strongly auto correlated time series, the value in any one time step is strongly influenced by the values in previous time steps, so long periods of high or low values emerge, as shown in part c) of Figure 7. Note that each data set in Figure 7 has the same average and the same Weibull *k* value. The degree of autocorrelation is the only distinction between the data sets.



(a) Wind Speed Time Series with no Autocorrelation (R_1 = 0.0)



(b) Wind Speed Time Series with Moderate Autocorrelation (R1 = 0.5)



(c) Wind Speed Time Series with Strong Autocorrelation (R1 = 0.96)

Fig. 7. The effect of autocorrelation based on wind speed and time

In addition to effect of autocorrelation based on wind speed and time, autocorrelation based on wind speed and lag was analyzed, the results were depicted in Figure 8. The purpose of doing this is to determine the presence of correlation between the values of variables that are based on associated aspects. On the average wind speeds have high autocorrelations, with a value of about 0.05 with a lag of 325. In the figure it was shown that as the lag increase average wind speed autocorrelation functions drops significantly. Some cyclic behavior was noticed in the wind speed correlations, with a period of several days. It is believed that this cyclic behavior is due to the minimum nonlinear wind speeds that are not decomposed.

The long term wind speed data were computed using Equation 5 above, a modified linear model was used, the solution to the linear model linear regression could be used the form:

$$y = a(xz)^b \qquad (8)$$

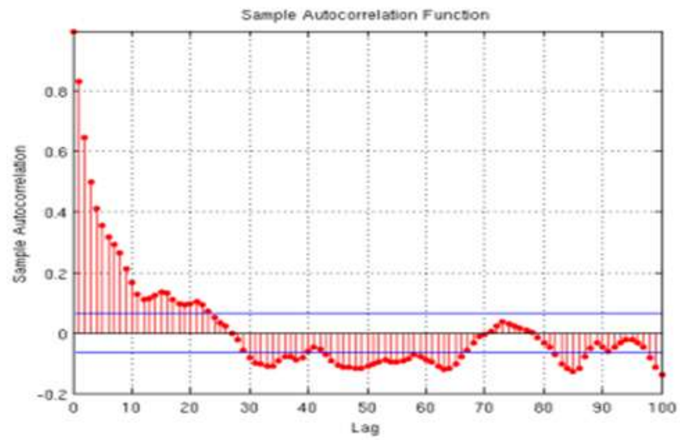


Fig. 8. Autocorrelation of wind speed.

In this case, the linear regression is performed after taking the logarithm of both sides of the equation. The values of the unknown were obtained using graph theory as shown in a scatter plot in Figure 9. The best generated solution with a = 0.677, b= 1.096 gives R^2=0.763 while 0.565 and 1.486 gives $R=0.894^2$. Hence, the coefficient of multiple determinations for multiple regressions with 0.894 was used to predict the long term wind speed.

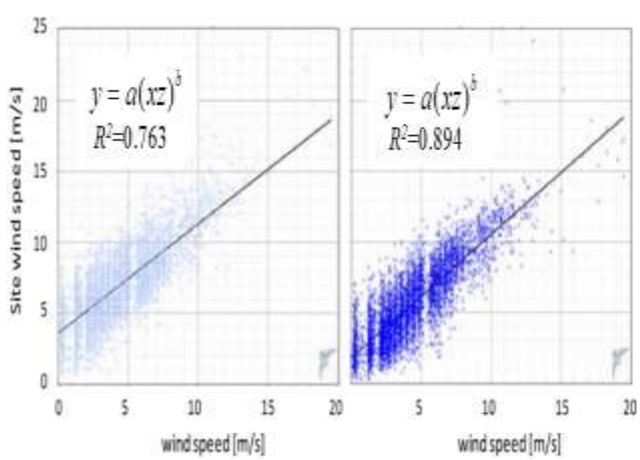


Fig. 9: Scatter plots for the long term wind speed

4.4 Predicted Wind Power Map of Sarawak at 20m Altitude

The average monthly wind speed in the target regions was computed, the wind speed varied from 3.74 to 2.68 m/s which is suitable for small scale wind turbine. The power density was the found and translates into a map as shown in Figure 10. It can be seen that, excellent regions are Kuching, Kota-Samarahan and Bau areas, However, Bintulu, Kapit, Miri Sarikei, SriAman, is moderate regions while, Limbang, Sibu areas marginal regions.

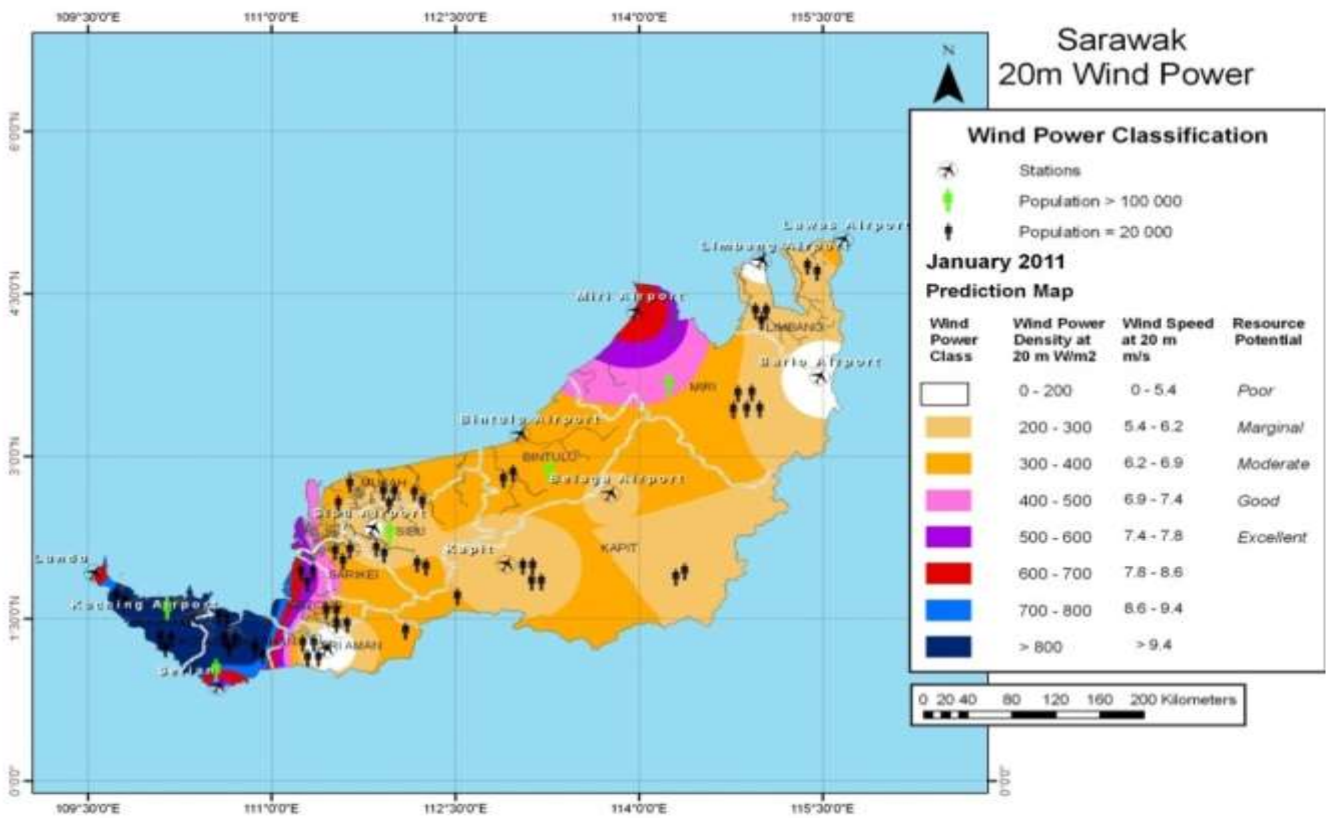


Fig. 10. Predicted Wind Power Isovents Maps

5. CONCLUSION

This paper shows an improve model of wind speed prediction. ANN was developed taking, terrain and roughness values into considerations. The model was trained, tested, validated and implemented using meteorological data available. To judge the suitability of the designed model, statistical measures were applied, in addition to comparison with conventional method. The model is found to be feasible with acceptable accuracy for wind speed prediction. The predicted and observed wind speed data were subjected to EMD in order to obtain the IMF wind speeds. The smaller wind values were applied to predict the long term wind speed using MCP techniques. The GIS was used to generate the wind energy mapping potential of Sarawak taking population data into consideration. In future studies, others anemometric values and terrain conditions could be considered.

6. ACKNOWLEDGEMENT

The authors wish to thank Universiti Malaysia Sarawak (UNIMAS) and Kano University of Science and Technology, (KUST) Wudil for supporting the research work under signed memorandum of understanding (MoU) on renewable energy parallel research work.

REFERENCES

[1] P. Gomes and R. Castro, "Wind Speed and Wind Power Forecasting using Statistical Models: Autoregressive Moving Average (ARMA) and Artificial Neural Networks (ANN)," International Journal of Sustainable Energy, vol. 1, 2016.

[2] GWEC, "Global Wind Energy Report," 2015.Avaliable online

[3] M. Islam, R. Saidur, N. Rahim, and K. Solangi, "Renewable Energy Research In Malaysia," Engineering e-Transaction, vol. 4, 2009.

[4] S. G. Portal. Demography, Geography and Economy [Online]. Available: http://www.Sarawak.gov.my/en/about

[5] Z. Abidin and I. Othman, "The future of hydropower in Sarawak, Borneo," 2005.

[6] M. Anyi, B. Kirke, and S. Ali, "Remote community electrification in Sarawak, Malaysia," Renewable Energy, vol. 35, pp. 1609-1613, 2010.

[7] S. M. Lawan, W. A. W. Z. Abidin, T. B. H. Masri, W. Y. Chai, and A. Baharun, "A Methodology for Wind Energy Evaluation in Complex Terrain Regions of Sarawak," International Journal on Electrical Engineering and Informatics, vol. 7, p. 264, 2015.

[8] S. Lawan, W. Abidin, T. Masri, W. Chai, and A. Baharun, "Wind power generation via ground wind station and topographical feedforward neural network (T-FFNN) model for small-scale applications," Journal of Cleaner Production, vol. 143, pp. 1246-1259, 2017.

[9] B. De Martino, D. Kumaran, B. Seymour, and R. J. Dolan, "Frames, biases, and rational decision-making in the human brain," science, vol. 313, pp. 684-687, 2006.

[10] D. C. Park, M. El-Sharkawi, R. Marks, L. Atlas, and M. Damborg, "Electric load forecasting using an artificial neural network," Power Systems, IEEE Transactions on, vol. 6, pp. 442-449, 1991.

[11] D. Spooner, S. Jarvis, J. Cao, S. Saini, and G. Nudd, "Local grid scheduling techniques using performance prediction," IEE Proceedings-Computers and Digital Techniques, vol. 150, pp. 87-96, 2003.

[12] R. A. Ball, L. C. Purcell, and S. K. Carey, "Evaluation of solar radiation prediction models in North America," Agronomy Journal, vol. 96, pp. 391-397, 2004.

[13] U. Focken and M. Lange, Physical approach to short-term wind power prediction: Springer, 2006.

[14] S. S. Soman, H. Zareipour, O. Malik, and P. Mandal, "A review of wind power and wind speed forecasting methods with different time horizons," in North American Power Symposium (NAPS), 2010, 2010, pp. 1-8.

[15] S. Lawan, W. Abidin, W. Chai, A. Baharun, and T. Masri, "Different Models of Wind Speed Prediction; A Comprehensive Review."IJSTRE 2013

[16] T. Akinci, "Short Term Wind Speed Forecasting with ANN in Batman, Turkey," Electronics & Electrical Engineering, vol. 1, pp. 41-45, 2011.

[17] H. Xiaojuan, Y. Xiyun, and L. Juncheng, "Short-time wind speed prediction for wind farm based on improved neural network," in Intelligent Control and Automation (WCICA), 2010 8th World Congress on, 2010, pp. 5891-5894.

[18] N. S. Çetin and C. Emeksiz, "Method Of Artificial Neural Networks With Parameter Estimating Wind Speeds Between Cities In Turkey," 2012.

[19] J. Lee, G. Park, E. Kim, Y.-c. Kim, and I. Lee, "Wind Speed Modeling based on Artificial Neural Networks for Jeju Area," International Journal of Control and Automation, vol. 5, pp. 81-88, 2012.

[20] Alkhatib, A, Heire. S., and K. M., "Detailed Analysis for Implementing a Short Term Wind Speed Prediction Tool Using Artificial Neural Networks," International Journal on

Advances in Networks and Services, vol. 5, pp. 149-158, 2012.

[21] J. Lorenzo, J. Méndez, M. Castrillón, and D. Hernández, "Short-term wind power forecast based on cluster analysis and artificial neural networks," in Advances in Computational Intelligence, ed: Springer, 2011, pp. 191-198.

[22] G. Giebel, R. Brownsword, G. Kariniotakis, M. Denhard, and C. Draxl, "The state-of-the-art in short-term prediction of wind power: A literature overview," ANEMOS. plus2011.

[23] S. Salcedo-Sanz, Á. M. Pérez-Bellido, E. G. Ortiz-García, A. Portilla-Figueras, L. Prieto, and F. Correoso, "Accurate short-term wind speed prediction by exploiting diversity in input data using banks of artificial neural networks," Neurocomputing, vol. 72, pp. 1336-1341, 2009.

[24] S. Pourmousavi Kani and M. Ardehali, "Very short-term wind speed prediction: A new artificial neural network–Markov chain model," Energy Conversion and Management, vol. 52, pp. 738-745, 2011.

[25] A. Kusiak, H. Zheng, and Z. Song, "Short-term prediction of wind farm power: a data mining approach," Energy Conversion, IEEE Transactions on, vol. 24, pp. 125-136, 2009.

[26] E. Safavieh, A. J. Ardakani, A. K. Kaviani, S. Pourmousavi, S. Hosseinian, and M. Abedi, "A new integrated approach for very short-term wind speed prediction using wavelet networks and PSO," in International conference on power systems, Bangalore, India, 2007.

[27] L. Dong, S. Gao, X. Liao, and Y. Gao, "Short-Term Wind Power Forecasting with Combined Prediction Based on Chaotic Analysis," Przegląd Elektrotechniczny Selected full texts, vol. 88, pp. 35-39, 2012.

[28] J. M. Sloughter, T. Gneiting, and A. E. Raftery, "Probabilistic wind speed forecasting using ensembles and Bayesian model averaging," Journal of the American Statistical Association, vol. 105, 2010.

[29] G. Sideratos and N. D. Hatziargyriou, "An advanced statistical method for wind power forecasting," Power Systems, IEEE Transactions on, vol. 22, pp. 258-265, 2007.

[30] M. Alexiadis, P. Dokopoulos, and H. Sahsamanoglou, "Wind speed and power forecasting based on spatial correlation models," Energy Conversion, IEEE Transactions on, vol. 14, pp. 836-842, 1999.

[31] I. G. Damousis, M. C. Alexiadis, J. B. Theocharis, and P. S. Dokopoulos, "A fuzzy model for wind speed prediction and power generation in wind parks using spatial correlation," Energy Conversion, IEEE Transactions on, vol. 19, pp. 352-361, 2004.

[32] T. Senjyu, A. Yona, N. Urasaki, and T. Funabashi, "Application of recurrent neural Network to long-term-ahead generating power forecasting for wind power generator," in Power Systems Conference and Exposition, 2006. PSCE'06. 2006 IEEE PES, 2006, pp. 1260-1265.

[33] Z. Guo, Y. Dong, J. Wang, and H. Lu, "The Forecasting Procedure for Long-Term Wind Speed in the Zhangye Area," Mathematical Problems in Engineering, vol. 2010, 2010.

[34] M. A. Lackner, A. L. Rogers, and J. F. Manwell, "The round robin site assessment method: A new approach to wind energy site assessment," Renewable Energy, vol. 33, pp. 2019-2026, 2008.

[35] J. Bass, M. Rebbeck, L. Landberg, M. Cabré, and A. Hunter, "An improved measure-correlate-predict algorithm for the prediction of the long term wind climate in regions of complex environment," 2000.

[36] K. XIAOBING, L. XIANGJIE, S. RUIFENG, and L. K. Y., Neurocomputing., vol. 169. Elsevier Science B.V, 2015.

[37] G. Li and J. Shi, "On comparing three artificial neural networks for wind speed forecasting," Appl. Energy, vol. 87, no. 7, pp. 2313–2320, Jul. 2010.

[38] N. E. Huang et al., "The empirical mode decomposition and the Hilbert spectrum for

nonlinear and non-stationary time series analysis," Proc. R. Soc. A Math. Phys. Eng. Sci., vol. 454, no. 1971, pp. 903–995, Mar. 1998.

[39] M. E. Torres, M. A. Colominas, G. Schlotthauer, and P. Flandrin, "A Complete Ensemble Empirical Mode Decomposition With Adaptive Noise." vol. 54, no. 678, pp. 789–798 Mar. 2018.

[40] M. Rezaie-Balf, O. Kisi, and L. H. C. Chua, "Application of ensemble empirical mode decomposition based on machine learning methodologies in forecasting monthly pan evaporation," Hydrol. Res., Nov. 2018.