Long-Term Wind Speed Forecasting and General Pattern Recognition Using Neural Networks

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***Abstract*—Long-term forecasting of wind speed has become a research hot spot in many different areas such as restructured electricity markets, energy management, and wind farm optimal design. However, wind energy with unstable and intermittent characteristics entails establishing accurate predicted data to avoid inefficient and less reliable results. The proposed study in this paper may provide a solution regarding the long-term wind speed forecast in order to solve the earlier-mentioned problems. For this purpose, two fundamentally different approaches, the statistical and the neural network-based approaches, have been developed to predict hourly wind speed data of the subsequent year. The novelty of this study is to forecast the general trend of the incoming year by designing a data fusion algorithm through several neural networks. A set of recent wind speed measurement samples from two meteorological stations in Malaysia, namely Kuala Terengganu and Mersing, are used to train and test the data set. The result obtained by the proposed method has given rather promising results in view of the very small mean absolute error (MAE).**

***Index Terms*—Artificial intelligence (AI), energy management, long-term forecasting, neural network, renewable energy, wind energy, wind speed.**

I. Introduction

A TWOFOLD significant challenge in the 21st century is to improve energy security and reduce the greenhouse gas emissions allied with energy consumption. One solution to tackle these challenges and achieving the goals of sustainable development, energy security, and environmental protection is to increase the role of renewable energy for electricity production. Since the natural wind is extremely variable, it is often described as an unreliable source of energy. In addition to this, if the risk and uncertainty level increases in expected generation, it will function as an inhibiting factor toward energy security [1], [2]. Therefore, improving prediction of energy output of a wind energy conversion system can help to reduce risks and enable assets to be operated in the most cost-effective manner. In other words, by applying accurate wind forecasting, the wind energy can be scheduled and wind power penetration will be increased. This has significant economic impact on the system operation and can substantially reduce costs [3]. Therefore, applying wind power prediction methods offering the best possible accuracy over a number of time scales is required [4].

As the output power of a wind generator is proportional to the cube of the wind speed, accurate estimation of wind output power is essential. Nonetheless, it is difficult to predict their future values with certainty [5]. In recent years, many research papers proposed the power prediction models to find an effective method in practical applications. These techniques mostly relied on complex statistics and artificial intelligence (AI) techniques and on applying large meteorological and topographic data [6]. Ideally, these methods are able to minimize the risk of failure within the energy system and forecast its reliability by modeling or simulating future scenarios. For example, to utilize the hybrid renewable energy systems with the storage battery, wind generators, solar cells, etc., the capacity of storage battery can easily be determined through prognosticated data, and it can potentially increase the efficacy level of hybrid power systems; however, their profitability depends on the accuracy of the prediction technique used, and it is notable that endeavours for research and development in this area are still continuing [6].

Since time series data on wind speed are chaotic, it is a very complex task to predict the wind velocity. Additionally, prediction accuracy is heavily dependent on the time interval as there is a negative correlation between accuracy and the increasing prediction time frame. A variety of methodologies have been proposed in the literature for the wind prediction, depending on the existing meteorological data and the time-scale of the application [7]. Generally, wind speed prediction is divided into three categories, namely, short-term, medium-term, and long-term predictions. Short-term prediction can refer to forecasting data of no more than a few hours ahead. The medium range forecasts are for a period extending from about a few hours to 3 days in advance. Long-term forecasts, being the subject of this paper, refer to a period greater than 3 days ahead; however, there are no absolute limits to the period. Long-term prediction of wind power may help switching between wind turbines or conventional generators, to achieve low spinning reserve and optimal operating cost [7].

The wind speed prediction model is basically classified into four categories: physical, statistical, AI, and hybrid methods [8]. The physical prediction method consists of some physical-based equations to convert meteorological data from a certain time, to the forecasted wind speed at a site considered. This method is considered as an effective way for long-term prediction.

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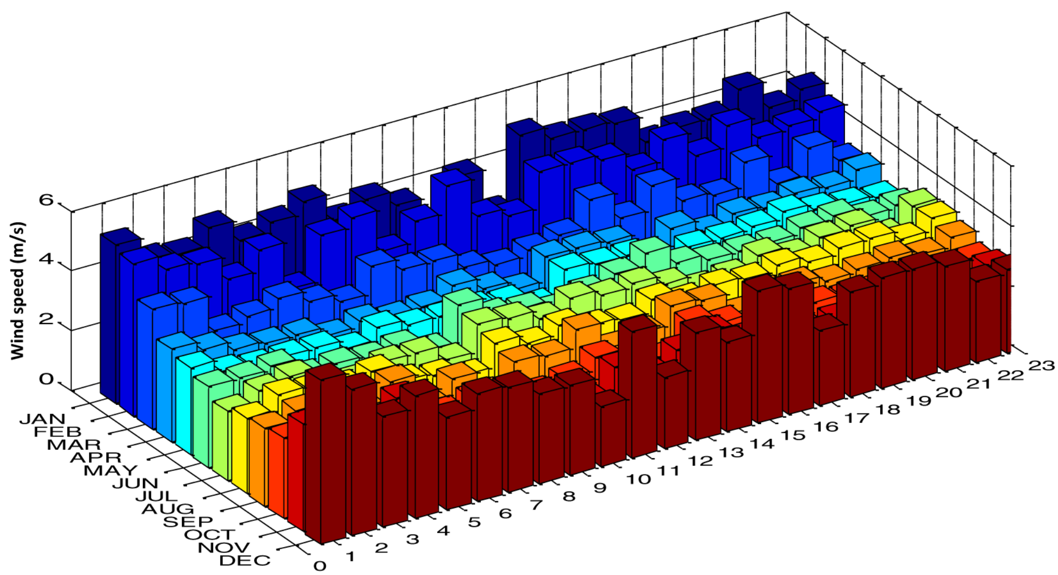

Fig. 1. Wind speed behavior in Mersing, Malaysia.

The statistical method is a patterns-based forecasting technique, which is an effective method for short-term prediction. In this approach, first the wind speed prediction model will be designed by using curve fitting and other parameters, and then the designed model will be adjusted by comparing the actual data in the immediate past and predicted one [9]. However, the statistical method cannot be utilized alone on long-term prediction. Instead, other methods such as numeric weather prediction, AI technologies, and hybrid approaches should be taken into consideration [3].

The AI approach is also an effective way to forecast wind speed data (WSD). The advantage of the AI method is to predict future times series data without any predefined mathematical models. The minimum probability of error can be achieved when the same or similar patterns are met. However, the accuracy drops significantly by extending the time horizon [3]. In the relevant literature that has been published recently, artificial neural networks (ANNs) have been widely used as a method of prediction and function approximation in nonlinear systems. Many researchers have applied ANNs for time series prediction of climatic variables in different time scales with satisfactory results compared to the traditional techniques [10]–[16]. This is because of their ability to handle noisy and incomplete data. Once they are trained, they can perform the prediction task and generalization at higher speeds [17].

The hybrid method uses one or more of each type of model in its predicting procedure to obtain the optimal forecasting performance and reduce the error. This method seems to be much more accurate when compared with other methods. This study also uses a composite method based on statistical and neural network approaches to predict hourly WSD of the year ahead.

The objective of this work is long-term prediction of mean hourly wind speed values in a region doable via applying a combination of different approaches. In order to identify the wind speed trend, a set of recognition sub-patterns is applied to monthly average WSD. Then neural network is applied on time-series data allied with recognized-pattern of the location to adjust the prediction. The algorithm does not require complicated calculations and mathematical complexity and does not require any data beyond historical WSD. It may also help managers of wind power plants to obtain greater economic profits. A set of recent wind speed measurement samples from two meteorological stations in Malaysia, namely Kuala Terengganu and Mersing, were used to train and test the data sets. It is believed that the general framework proposed in this study can be applicable in a variety of decision-making situations.

II. Wind Energy in Malaysia

The seasonal variation in Malaysia is conventionally expressed by four climatic seasons, namely first inter-monsoon (April), southwest monsoon (mid-May to September), the second inter-monsoon (October), and the northeast monsoon (November to March) [18]. The wind does not blow uniformly in the early and late parts of the year. Wind speed during the southwest monsoon is generally below 7 m/s, but during the northeast monsoon would be up to 15 m/s, particularly in the east coast of Peninsular Malaysia such as Mersing, Kota Baharu, and Kuala Terengganu [19]. The maximum speeds occur in the afternoon and minimum speeds occur just before sunrise [20]. Fig. 1 shows the wind speed behavior in Mersing over a period of 23 years, that is, from 1988 to 2011. The figure demonstrates the monthly mean wind behavior and seasonality factor of wind speed pattern, as mentioned above. In this paper, a general path is estimated for the next year by studying the wind speed characteristics in two stations in Malaysia and then the hourly wind speed is predicted.

III. Methodology

A. Forecast Error Indicators

In general, the performance of the prediction model is evaluated by a variety of indicators. In this study, mean absolute error (MAE) is selected to calculate the forecasting error.

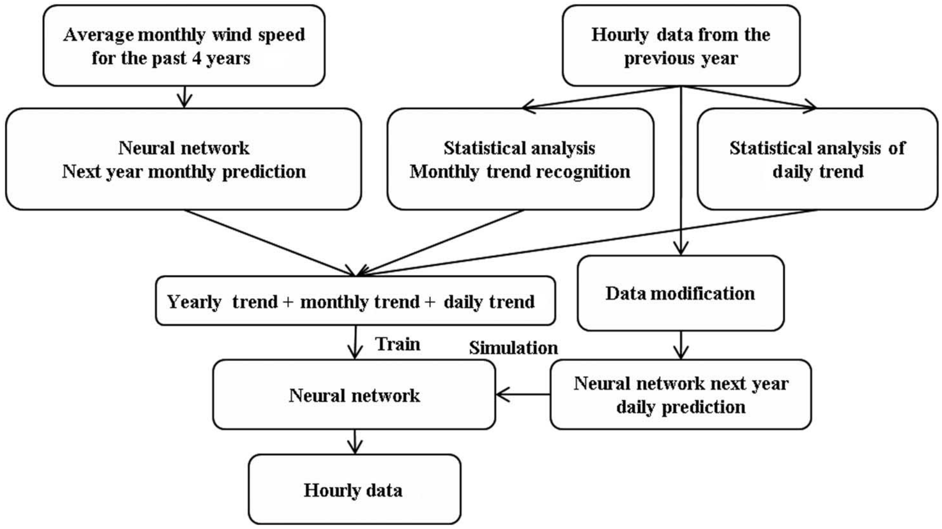

Fig. 2. Procedure in the proposed model.

1) Mean Absolute Error: MAE is an average value of the absolute errors $e_i = |P_f - P_a|$. It is used as a common indicator to measure the forecast error. It is given by

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N} |e_i| \tag{1}$$

where N is the number of data, e_i is absolute error, P_f is forecast value, and P_a is actual value.

B. Design of ANNs Model

The main idea of this paper is to predict the hourly WSD of the year ahead by studying the wind speed characteristics of specific regions and finding the pattern of wind speed variations. Because of the intermittent nature of wind, prediction for such kinds of data requires special care and no typical patterns can be directly found from the data [3]. In addition, study of average monthly wind speed from the past 23 years in Malaysia shows that it does not follow any special patterns; however, it may be predicted by using a combination of ANNs and some statistical approaches. The procedure of the proposed model can be summarized as in Fig. 2.

In brief, the general path for the next year is predicted using only the historical data of the actual wind speed of 1 year ahead and average monthly WSD for the last 4 years; however, it would not be appropriate and needs some modifications. For this reason, the general trend of the previous year, as the input and the actual hourly data as the target, will be used to train the network and update the neurons' weights in the neural network, and then the general trend of the predicted year can be simulated by using the trained neural network. The result has shown a significant improvement on long-term predictions of wind speed. The following paragraphs describe the aforementioned method in more detail.

Step 1) Annual Wind Speed Prediction: In the first stage, the average monthly wind speed of the coming year is forecasted by using the nonlinear autoregressive network with exogenous inputs (NARX). In the architecture of NARX neural network, the estimated output is always compared with the true value, and because of this criterion, the output is more accurate for time series predictions. It predicts series $y(t)$ by storing both the past obtained values of output as feedback and the input, $x(t)$ (Fig. 3). The proposed model in this study used the average monthly WSD of the past 10 years to train the network (4 years as input, 2 years as delays, and 4 years as target). The output predicts the average monthly wind speed of the next 4 years. To find the best prediction, the results are examined, and if the error from past 3 years is less than 0.6 m/s, then the predicted year will be accepted; otherwise, the training will be repeated until it reaches the desired output. (The block diagram is displayed in Fig. 4.) Fig. 5 shows the annual predicted wind speed versus the actual data; the first 3 years are used to evaluate the prediction results, and if the error is less than 0.6 m/s for the period of 3 years, then the fourth year which is the predicted year will be accepted.

Step 2) Monthly Wind Speed Prediction: Since the pattern of wind speed may have wide variations from the previous year wind speed, the statistical methods cannot help to find or predict the pattern of wind speed. Fig. 6 shows the monthly trend of wind speed for a period of 23 years, and an interpolation method is used to fit a curve to the WSD. In this method, the interpolating function passes through all the data points, so this can make a clear picture of the periodic characteristics of the wind speed for each individual month. Since there are some periodical variations on the pattern, they can be predicted by applying the neural network for every month. Generally, time-series-based models are applied in the literature; however, results of any unsatisfactory performance indicate that the ability of these models will decrease by increasing the time periods for medium- or long-term predictions [9]. In this study, the monthly pattern of wind speed is forecasted by using two feed-forward back propagation networks; they consist of two

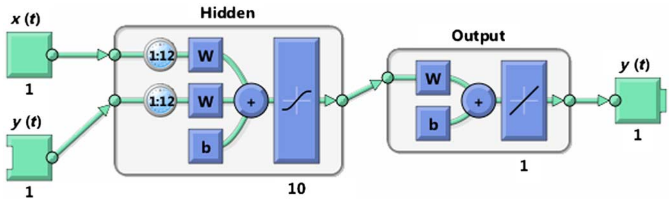

Fig. 3. Architecture of NARX neural network.

layers with 6 and 15 neurons, respectively. The inputs of the first network are average hourly WSD of the first 6 months from previous years. The network is trained for the next 6 months and then it is used to predict the WSD of the first 6 months of the coming year. The second network is trained for second half year to predict the WSD of the last 6 months of the coming year (Fig. 7). However, for better prediction, some data modification is needed. In this study, two data methods for data preparation are used before training the networks. It is observed that in time series data, the minimum probability of error can be achieved when the same or similar patterns are met [3]. For this reason, the data in the second half year are reversed and the input of the network for training and simulation will become almost similar. Then the sample cross-correlation function is helpful for identifying lags between two time series. Using this function, we can identify the amount of shifting between input and target in the neural network and make our time series more symmetrical. However, the time series cannot ideally become symmetrical. As we test data shifting on different periods and using different neural networks, we find that this method combines with mirror function (reversed function) and can decrease the error up to 50% in time series data. As it can be seen from Fig. 8, the plot shows significant correlation at lag −32. Therefore, time series data shifted for about 1 month to make time series data symmetrical for 1 year. However, after training and simulation, shift the origin back to the original position.

Step 3) Daily Wind Speed Prediction: Then, the daily pattern of wind speed is extracted from hourly WSD of the previous year (Fig. 9). First, the average hourly wind speed is calculated for each hour a day using meteorological data from last year. Then, the data set was normalized according to the following equation:

$$\text{Wind speed}\,(\text{h}) = \frac{\sum_{\text{day}=1}^{360} \text{wind speed}\,(\text{day}, \text{h})}{360 \times \text{average wind speed}\,(\text{h})} \quad (2)$$

Step 4) Pattern Recognition: As it is illustrated in Fig. 10, a general pattern of the next year is constructed using a nested combination of three subsections [steps 1)–3)] [21].

Step 5) Pattern Recognition: A general pattern of the wind speed for the previous year also has been extracted from the hourly WSD by applying the same procedure.

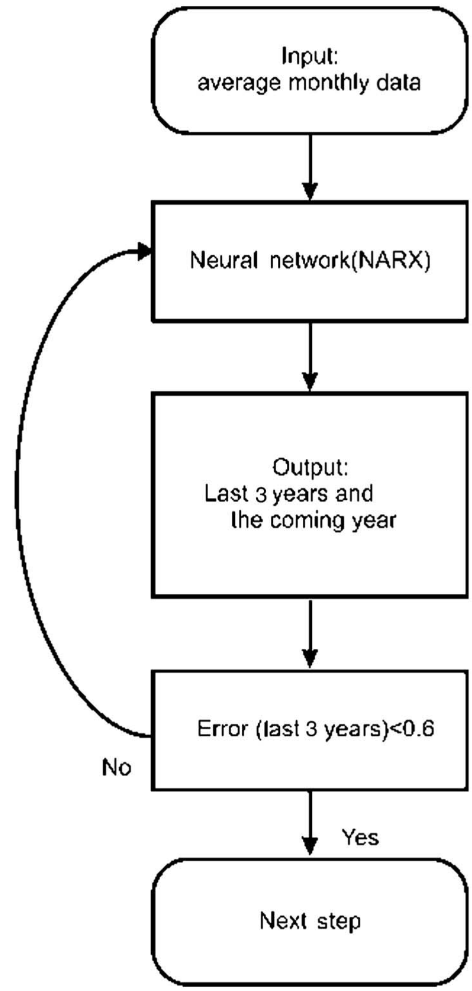

Fig. 4. Annual wind speed prediction.

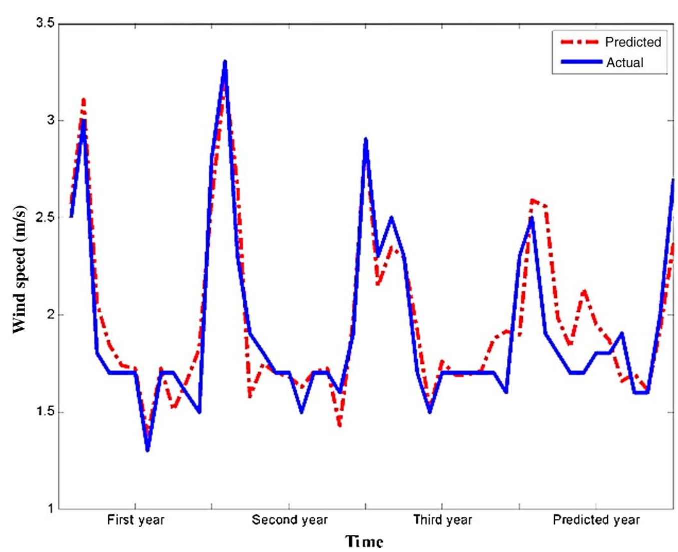

Fig. 5. Predicted wind speed versus real data in Kuala Terengganu, Malaysia.

Step 6) Hourly Wind Speed Prediction: The general path of the last year and the actual hourly data are used as the input and the target to train the network and update the neurons' weights, and then the general path of the

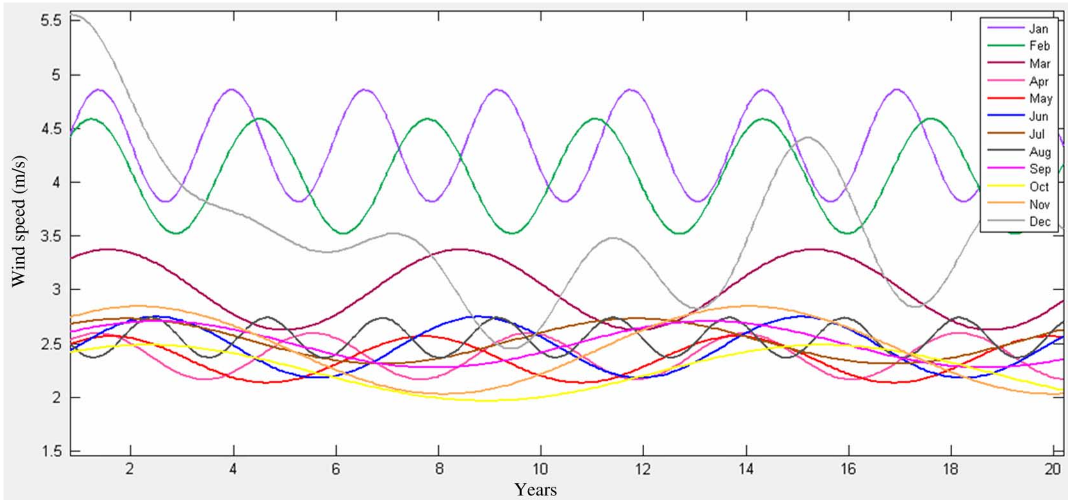

Fig. 6. Monthly pattern of wind speed for 23 years.

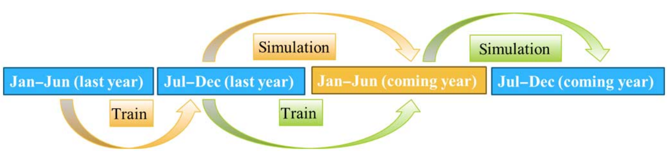

Fig. 7. Monthly path prediction.

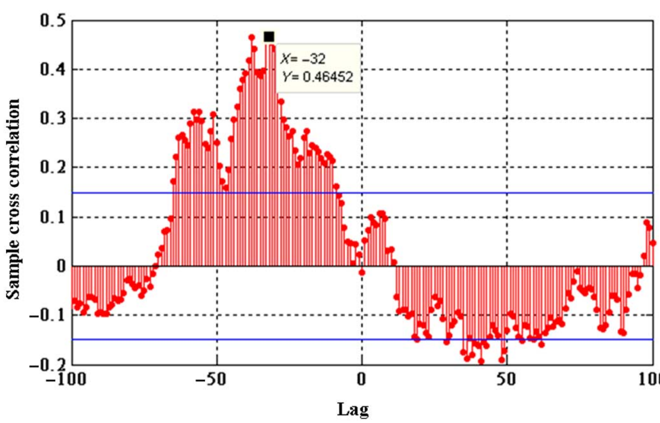

Fig. 8. Sample cross-correlation function.

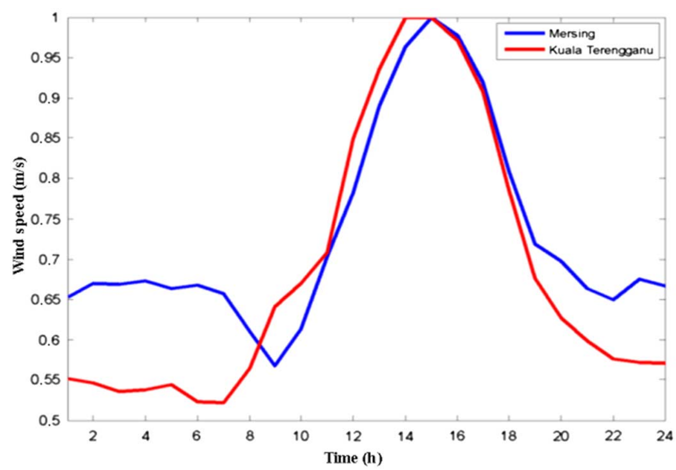

Fig. 9. Daily pattern of wind speed.

predicted year could be obtained by using simulation methods (Fig. 11). The result shows a noticeable improvement in the long-term predictions of wind speed.

IV. Results and Discussion

The proposed model has been tested for two different stations in Malaysia and compares with feed-forward, time delay, Layer-Recurrent, and nonlinear autoregressive neural networks. MAE is used as an uncertainty measurement indicator to assess the risk of trusting in the prediction. Annual wind speed is forecasted by using the nonlinear autoregressive network with exogenous inputs (NARX). The monthly pattern of wind speed is predicted using two-layer feed-forward back propagation networks with 6 and 30 neurons in the middle and the output layers, respectively.

It has been found that feed-forward back propagation networks can perform better than time series neural networks for long-term prediction; however, time series neural networks are common methods in short- and medium-term predictions.

Eventually, the daily pattern of wind speed is extracted from previous data to develop the general pattern of wind speed in the subsequent year. To predict hourly WSD, another two-layer feed-forward back propagation network with 30 and 12 neurons in the first and second layers is applied, respectively. The neural networks are developed and optimized using 8 years of average monthly WSD and only 1 year hourly data. The obtained accuracy of the optimal configuration is around 0.8–0.9 m/s for MAE.

The result compares with several wind speed forecasting methods that have been developed in the literature over the past few years. Feed-forward networks can be used in a variety of applications to fit input and output, using enough neurons in the hidden layers [22]. Time delay neural network can work effectively on time series prediction. It is similar to the feed-forward

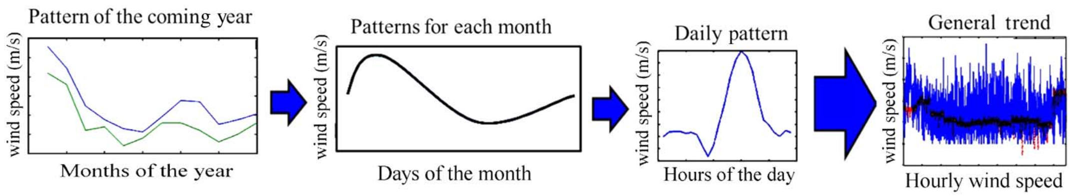

Fig. 10. General procedure of trend recognition for the coming year.

TABLE I
RESULTS AND COMPARISON

Time step	Method	MAE (minimum)	
		Mersing	Kuala Terengganu
Monthly mean wind speed	**Proposed method**	0.24	0.17
	Time delay neural network	0.47	0.45
	Feed forward network	0.36	0.73
	Layer-Recurrent Network	0.95	0.48
30 Days ahead	**Proposed method**	0.80	0.64
	Time delay neural network	2.34	0.88
	Nonlinear autoregressive neural network	2.21	0.90
	Feed forward network	1.89	0.88
	Layer-Recurrent Network	1.93	0.89
1 year ahead	**Proposed method**	0.94	0.80

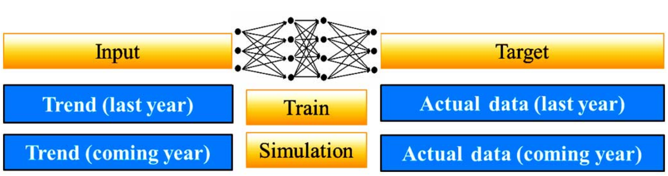

Fig. 11. Long-term wind speed forecasting.

network, except that it has a finite dynamic response to the time series input by using a tap delay line associated with input weight. The nonlinear autoregressive neural network with external input is a recurrent dynamic network that uses the output as a feedback to input [6]. The layer-recurrent network has a feedback loop, with a single delay, around each layer of the network except for the last layer, and it can be applied for modeling and filtering applications; however, it is recommended for long-term WSD forecasting by Olaofe and Folly [22].

The trial-and-error method has been used to determine the appropriate number of hidden neurons. It starts with a few numbers of neurons and gradually increases to 28 neurons while training the networks until it reaches the lowest error [6]. The optimized number of neurons for the feed-forward network is 4 and 9 in input and hidden layers, respectively, and 10 for time delay and autoregressive networks.

By comparing the results with other wind speed forecasting methods in Table I, it can be seen that the result obtained by the proposed method has given rather promising results in view of the very small MAE.

However, there are some limitations for the proposed method and the results still need some improvement to increase the accuracy of the prediction. According to the obtained data, there is a positive correlation between the wind speed variation and the increased error associated. Although the proposed method follows the general identified trend, it is less likely to have a high percentage of error, which is a common problem occurring in long-term prediction of wind speed.

Fig. 12 shows the predicted wind speed in step 1) as compared to the actual wind speed obtained from the Malaysian Meteorological Department. As can be seen in Fig. 12, the errors are well within 0.5 m/s; however, the performance derived from neural network can be slightly different on different runs. The MAE outcomes of average monthly wind speeds are about 0.17–0.36 m/s in Kuala Terengganu and about 0.24–0.38 m/s in Mersing, which have shown an improvement over the existing works.

More than 51% of the estimated values in Mersing and more than 75% of estimated values in Kuala Terengganu shows the error less than 1 m/s; however, at some points, the errors would be more than 8 m/s, which is not desirable and can highly affect the wind power prediction. In order to avoid such errors or adapt the result within a specific region, the proposed result can be periodically modified based on the real meteorological data in the target year. It is also recommended that the prediction model can be updated periodically by using the difference between the predicted and actual WSD in the immediate past and consequently the result would be

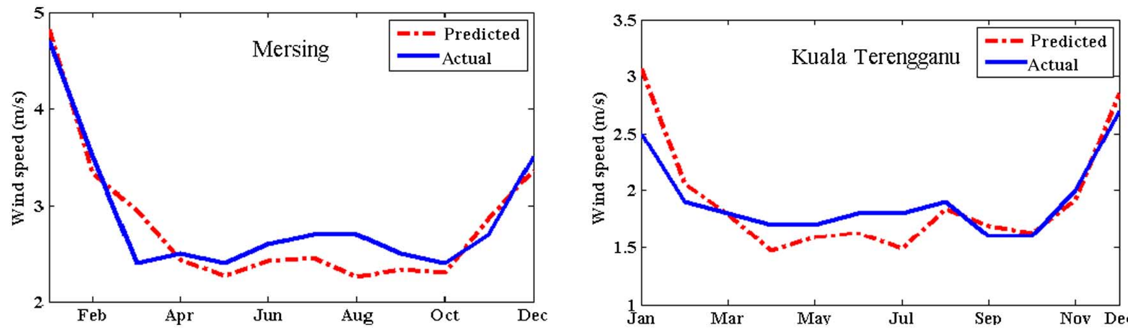

Fig. 12. Predicted wind speed versus the actual wind speed for 1 year ahead.

improved. More comprehensive forecast methods are being investigated by the authors of this paper to increase the accuracy of long-term time series prediction.

V. Conclusion

In general, accuracy in wind speed forecasts is crucial for a number of operational, engineering, scientific, and financial reasons. The objective of this work is long-term forecasting using hybridization of different optimization approaches. The novelty of this study is to forecast the general trend of the coming year by studying the characteristics of the wind speed for the past few years, which can significantly improve the results of long-term predictions. Moreover, a novel data preparation is also suggested to increase the accuracy of the prediction. In order to identify the wind speed trend of the coming year, a set of sub-patterns are recognized and applied accordingly to the monthly average WSD. The time series data are applied to a neural network allied with the recognized pattern of the location to adjust the prediction. A set of recent wind speed measurement samples from the two meteorological stations in Malaysia, namely Kuala Terengganu and Mersing, were used as training and testing data sets.

The results demonstrate that the proposed model improved other existing forecasting models for long-term wind speed prediction. For example, in terms of MAE, the recommended model indicates about 0.8 m/s for MAE. By comparing the actual and predicted WSD, it can be seen that the hybrid technique can follow actual series closely. Therefore, it can be effectively used as an appropriate alternative model for long-term wind speed forecasting tasks, as it follows the general identified trend in the prediction procedure.

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