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Hybrid Wind Speed Prediction Model Using Intrinsic Mode Function (IMF) and Gradient Boosted Machine (GBM)

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Abstract: Before sitting a wind turbine, reliable wind speed prediction is prerequisite requirements that must be performed in order to get optimum energy yield. Single model has a lot of constraints in terms of prediction accuracy, to solve this persistent problem, this paper presents the application of hybrid model based on IMF and GBM so as to predict the wind speed in the areas with limited or absent of data. In the first place, the observed wind speed was decomposed into six using IMF in order to reduce ill-define stochastic nature of wind speed. The decomposed wind speed was used to train, test and validate the model developed GMB model which was developed in a Matlab environment. 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 2017 to 2018 were used for the simulation. The model implementation confirmed that the proposed model is robust and capable to predict wind speed in remote and rural areas. A comparison with conventional method (ARIMA) was further investigated, the results showed the superiority of the new hybrid model over ARIMA.

Keywords: Gradient Boosted Machine (GBM), instinct mode function (IMF), prediction, Sarawak, wind speed

1. Introduction

It is generally known that the current system of energy generation based on limited resource fossil fuels (Coal, Gas and Petroleum) is not sustainable. Because the resources are finite, they are discovered and utilized. That is why most of the countries around the world have realized the current scenario of energy using dirty source is generating environmental worries such as greenhouse gases (GHG, acid rain etc. furthermore, increase in population and urbanization has raised the energy demand and consumption, but unfortunately, the fossil fuels are not evenly distributed around the world. The listed problems has necessitated searching of an alternative sources, that will be used today and tomorrow without compromising the future needs of energy. Among the clean sources (solar, hydro, fuel cell, wave tidal, geothermal, thermo electric generator), wind energy has emerged as the oldest technology applied by mankind to solve remote and immediate problems. In recent times, wind energy is become popular for electrical power generation in both grid-tie and non-grid mode. Wind energy is an indirect solar energy, the merits of using this resources is the wind availability in day and night. The potential of its development is huge, since the world's capacity is far larger than the world's total energy consumption [1]. Recent publication of wind energy association has shown that the wind energy is currently at boom stage, as more countries of the world developing medium and large wind energy farms. As a new global high-tech sector, more countries are taking advantage of this untapped source of renewable energy. Malaysia is trying to develop a reliable energy mix that will boost it economic, and urbanization

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vision. Generation of electrical energy via clean and affordable source is one of its major policies in fifth fuel diversification policy. Wind energy development in small scale is also given a priority. Because the country is strategically situated in the low latitude where wind speed strength is moderate. Though, the country wind speed falls within marginal values, the wind energy could be used for rural and remote areas application, especially in the areas with low sunshine hours and low head rivers.

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 power results in savings of 0.5 to 1 tons of greenhouse effect gas. 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 2008-2018 [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 Application of wind power is rapidly growing in many countries of the world, 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 2019 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 268,690MW, 32,700MW, 4,234MW, 982MW, 631MM and 56MW respectively]. The rest of the country 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 [2].

Sarawak is among the two States of Malaysia located in the Island of Borneo. The province has a population of about 2, 400,000 with a dense concentration of 22 people per square kilometer due to its large field. The State is located between 109°36'E and 115040'E of longitude and 0°N and 5^0N latitudes at a height between 400 to 1000 m above mean sea level. It has a total land area of approximately 124,000 square kilometers, which is almost equivalent to the total area of the other states forming the Malaysia Peninsular [3].

Rural and remote people of Sarawak on the average settled in small villages comprising of approximately 20–40 families. A few bigger villages of up to 200 families can also be found. The rural and urban ration has narrowed markedly, with 51% of Sarawak population lives in the rural and remote areas. Many of the rural areas are only easily reached by logging road, plane or river transport [4]. Those areas are so remote that is not economically feasible to step down the high voltage transmission that passed through them. Another problem is that, the existing wind stations are located in the cities were principal interest in renewable energy is minimal.

Due to geographical settings of Sarawak, coupled with the need to provide electricity easily, renewable energy system such as solar, hydro and wind are natural sources of energy that can be applied in non-grid connected mode. In order to supply electrical energy to rural/remote areas of Sarawak, small-scale wind power driving system can be applied easily [5].

Motivated by the above discussions, this paper goal is to forecast the wind speed values and also to develop a wind atlas map for Sarawak based on available wind station data and hybrid soft computing model. The remaining part of the paper is arranged as follows: section 2 presents a general overview of wind speed prediction models, proposed implementation strategies are presented in section 3, follow by the outcomes of the study, comparisons and discussion in section 4, finally section 5 concludes the paper.

2. Previous Works for Wind Speed Prediction

Prediction techniques are widely useful in engineering and econometric applications. A lot of approaches on prediction have been implemented and presented in scientific literatures. Prediction outcomes in decision making conducted [6]. Electrical power load prediction model performed by [7]. Performance prediction for local grid scheduling [7]. Many types of solar irradiance prediction models have been developed and utilized [8]. Wind speed prediction is more tedious compared to other predictive techniques like solar, electrical load and local grid scheduling, due to complexity, stochastic and ill-defined nature of wind speed values. Wind speed prediction models can be catalogued into two different groups depending 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), machine learning, deep learning and fuzzy logic control. Artificial neural network (ANN) and statistical modeling [9]. An extensive review on wind speed prediction with different time horizons can be found in [10-11].

2.1 Wind Speed Prediction: Short-Term

It was reported in many works that, short time wind speed prediction got considerable attention in planning wind power projects. Short-term wind speed prediction using the ANN model has been applied in Batman, Turkey, [12] 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, [13] 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 Jia et al. [19] developed and evaluated a wind speed model and performed data analysis. Detail reports for the design and development of short-term wind speed using ANN have been systematically discussed in [19].

Authors [14] have developed an architecture for estimating short term wind speed by applying a methodology of 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 were used for short term prediction based on Radial Basis Function Network and Kernel Machines [15]. 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, [16] 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 developed 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 [18]. 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 [18], 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 [18]. Chaotic time series analysis and SVM regression have been presented in [10]."The RRMSE 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 [19]. This method provides quick and standardized probabilistic prediction compared with other numerous formulations. A combination of RBFN and fuzzy logic techniques are applied for a wind speed estimation in [20], the test result shows that it can be used effectively for predicting short time wind speed. Wind speed prediction based on spatial correlation and a hybrid fuzzy model for wind speed using spatial correlation [21].

2.2 Wind Speed Prediction: Long -Term

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: Long term memory network (LTMN) [22], first definite seasonal index method and the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) proposed in [7], the predicted errors were compared to the ones achieved from GARCH, ARMA and SVM. The developed hybrid system is efficient and simple for predicting average daily hour wind speed. Measure-Correlate-Predict (MCP) techniques were reported in [23]. An improved MCP method that integrated ANN has been presented by [24].

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. A recently published work in the area of wind speed decomposition used wavelet and wavelet neural network to ensure optimum prediction is achieved. Though, the work introduced Cuckoo search algorithms to optimize the developed model [25]

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 model (IMF+GBM) is proposed. Multiple wind stations are considered in this research. Spearman rank correlation is used to test and select the best strength wind speeds, and then, the time series wind speed was fragmented into finite samples of empirical modes which is referred to Intrinsic Mode Functions (IMF) and coupled the fragments into the GBM so as to perform training, testing and validation.

3. Methodology

3.1 Wind Speed Signal Decomposition and GBM Implementation

Empirical mode decomposition has emerged as new techniques in random process and random variable techniques in dealing with random variables such as wind speed. Wind speed is non-linear, non-stationary variable. EMD is among the optimized ways reduce the ill-defined nature. The fragmentation of wind speed into low frequency fragments of a time series is called EMD, the partition can be performed using different approaches. In this paper Intrinsic mode functions (IMFs) was carried out. That is the wind speed was decomposed into smaller frequency. But in this paper mixed mode fragments was considered, that is frequency and time domains were considered. The purpose of doing this is to compare Fourier transform and wavelet decomposition. That is time and frequency analysis was carried out. EMD is not based on physics study here but to provide insight of various signals contained in the data. This technique helps to analyze natural signal that are ill-defined in nature [26] To decompose an ill-defined variable into IMF, EMD has emerged as best tool with fewer errors. The merit using this method is the frequency and time functions are obtained from the main signal. In this study, the wind speed *x(t)* was decomposed using Equation1:

Many researchers have applied IMF to predict wind speed [27]. However, the quality of the prediction method used lies on several factors such as determination of optimal parameters. in a recently published work applied tree gradient boosting machine to solve three multi-step wind speed prediction model [27-28]. The conventional approach used to deal with time series wind speed data is to decompose the original wind speed into smaller frequencies in order to reduce the non-linearity, before applying it to predict the future wind speed. In this paper a slight modification was made, GBM coupled with IMF was applied to predict the wind speed. But only small frequencies wind speed data was utilized.

For a series x that undergoes IMF decomposition into approximation series. $A_j, j = 1,2,3.....n$ and $D_j = 1,2,3,....n$ it can be represented by:

$$x = A_n + \sum_{i=1}^{n} D_i \tag{1}$$

Once the wind speed is decomposed, the decomposed wind speed level will be terminated depending on the instinct and empirical relationship as shown in Equation 2:

$$\frac{SD(A_j)}{SD(x)} \leq 0.1 \tag{2}$$

where *SD* is the standard deviation, A_j means the approximation component at the j_{th} decomposition level, and x is the original series.

The smaller frequency wind speed is used to establish a network for each sub-series. The IMF+GBM was applied as a sub-set model to predict the optimized parameters using gradient boosts tree algorithm.

The algorithm used is described below:

Let N j be the sub-forecasting model of Dj, j = 1; 2; ... ; n,

N n+1 be the sub-forecasting model of An.

Detailed of the algorithm process is shown in Fig. 1 which shows the decomposed GBM and the reconstruction parts. The model input is the wind speed, while the final output is the predicted wind speed. The multi-level prediction results is given as a vector $\hat{x}$ expressed by:

$$\hat{x} = \sum_{i=j}^{N} N_j(D_j) + N_{n+1}(A_n) \tag{3}$$

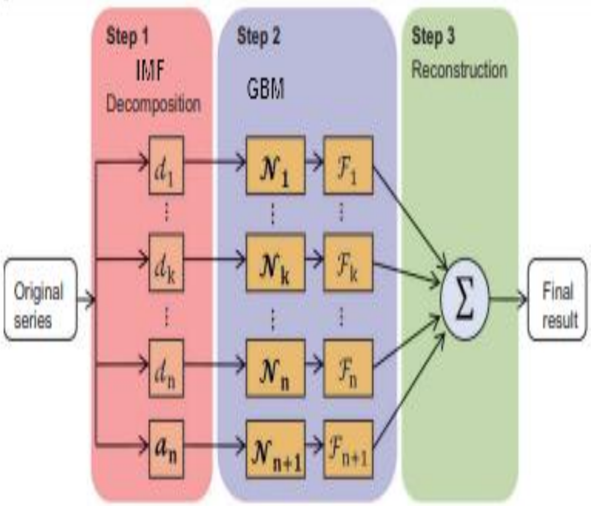

Fig. 1 - The framework of the model

The evaluation criteria used to judge the suitability of the developed approach are four criteria to evaluate the forecasting efficiency of the two models: the mean the root-mean-square error (RMSE) (Equation (4)), and the Pearson correlation coefficient *(r)* (Equation (5)):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(X_{obs,i} - X_{model,i})^2}{n}} \tag{4}$$

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})\cdot(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \cdot \sum_{i=1}^{n}(y_i - \bar{y})^2}} \tag{5}$$

3.2 GBM Methodology

In the era of soft computing, GMB is a numerical optimization approaches which is used to find an additive model that will minimize the loss function. Hence, the GBM is an iterative procedure which adds a new decision at each step so as to reduce the loss function at each step based on new decision before moving to the next step. The steps used in this paper, guess regression algorithm was first used in order loss function (that is regression mean squared error). In the next step a new decision tree is used to fit the residual, and then added to the previous model so as to update the residual function. The procedure continues to iterate until the maximum of iteration provided is reached. In this paper a maximum number of iteration is set 1000. The purpose of doing this is to ensure optimum parameters are achieved. The process is depicted in Fig 2.

Step 1: Selection Stage:

1. *Decision tree depth is d*
2. *Iteration is k*
3. *Learning rate α*
4. *Sample fraction in the Subsets (η)*

Step 2: Initialization Stage

1. *Residual is set to $r_0 = y$ and $f = 0$.*
2. *The initial guess is the mean value of y*

Step 3: Do loop Steps

1. *For $k=1, 2, 3 \ldots\ldots K$ Do the following*
2. *Select from the subsets randomly (x_i, y_i) from N training datasets from the corresponding fraction data points*
3. *Using (x_i, y_i) decision tree, depth d and residual*
4. *Update by adding decision tree to the model*
5. *Update the residual*
6. *Stop*

Fig. 2 - A simplified illustration of this algorithm is provided by the following pseudo-code:

4. Results and Discussion

The decomposed wind speed based on the IMF was performed as stated in the methodology section. Fig, 3 shows the seven IMF functions including one residual function, for a period of one year, it is clear that the wind speed is non-stationary, even though, the wind speed is positive IMF_1 shows a high oscillation with high frequencies, while IMF_2-IMF_5 vary slowly and symmetrically. It can be seen that in Fig. 4, the nonlinearity properties of wind speed reduces from the original signal as IMF increased, at IMF_4 and IMF_5 the stochastic behavior of wind speed decrease from the original signal as IMF increased, at IMF4 and IMF5 the wind speed ill-defined nature was lowered. The IMF wind speed was then utilized during the model operationalization. Fig. 3 and Fig. 4 illustrate the prediction results for the two cases during the monsoon, respectively. Taking each case separately and forecasting horizon, the graphs that analogize the outcomes of the designed hybrid structure and discussion are marked as (a) scatter diagrams that collate the designed model with the experimental result as (b), (c), and (d). Table 1 indicates the mean percentage errors obtained for different experimental tests conducted in three seasons.

As depicted in Table 1 and Fig. 4, the forecasting fact decreases when the prediction horizon increases in all the designed models in both two cases (case1 and case2). For instance, the RMSE of IMF+GBM case1 1+t, 3+t and 5+t is 0.5772, 0.55385, and 0.5627, in every case. Likewise, the results found by the second models and case2. The outcomes indicate that IMF+GBM surpass the entire designed hybrid models. Fig. 4 shows the results of decomposed wind speed while, the error results shown in Table 1. As shown in the figure the IMF + GBM produce better results when cross check with the other models. ARIMA acts poorer in the case 2 models. The values of RMSE and Pearson correlation coefficient are smaller in case 1. The average RMSE and Pearson correlation coefficient are 0.5594 and 0.9489 respectively.

Table 1 - Model Results: *RMSE* and *r*

Case	Model	*RMSE*	*r*
Case 1	IMF+GBM	0.5772	0.9821
	ARIMA	0.9942	0.849
Case 2	IMF+GBM	0.5385	0.9383
	ARIMA	1.2332	0.6684
Case 3	IMF+GBM	0.5627	0.9264
	ARIMA	0.9279	0.8598
Mean	IMF+GBM	**0.5594**	**0.9489**
	ARIMA	**1.0517**	**0.7587**

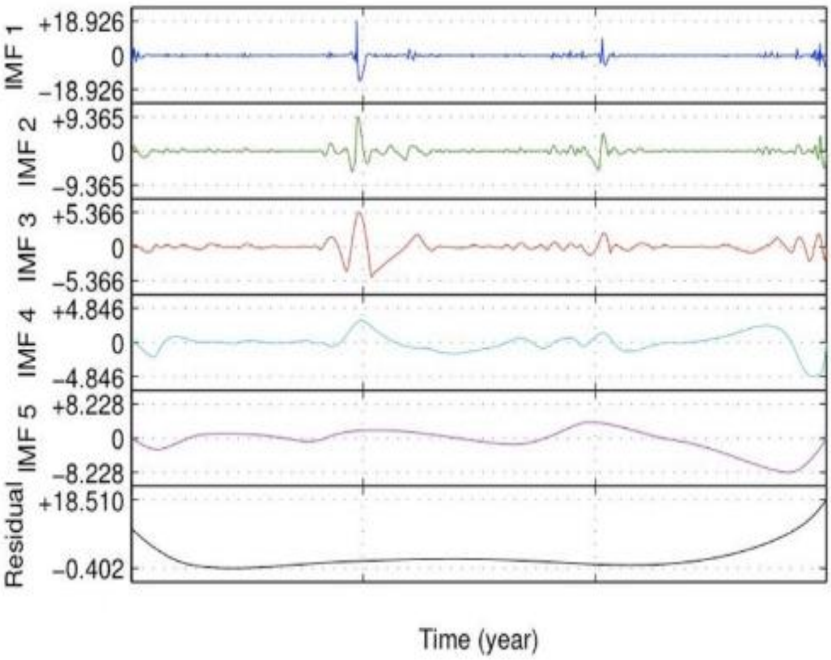

Fig. 3 - Decomposed wind speed IMF1-IMF5

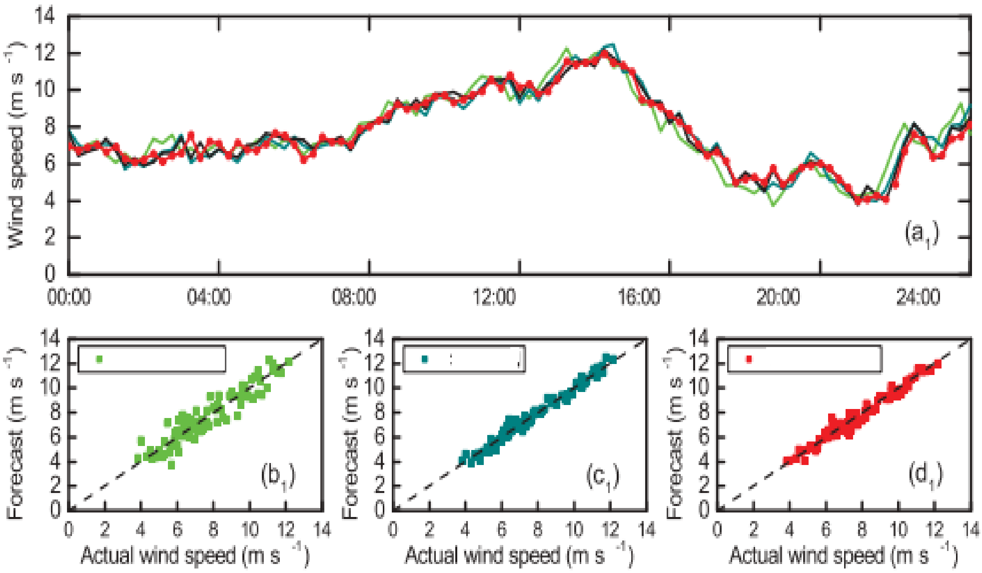

Fig. 4 - Wind speed forecast results (a) IMF+GBM and ARIMA, b (Case 1) c (Case 2) and d Case (3)

5. Conclusion

This paper shows an improved wind speed prediction using multi step hybrid model. A methodology was developed to predict wind speed using IMF and GBM for proper planning of wind energy. An optimized methodology was applied to each step with the help of gradient-based tree algorithm. Using hybrid model (IF+GBM), the wind speed was decomposed into smaller frequencies. The smaller wind speed was used as model input, and then gradient tree algorithm was used to optimize the parameters before the final predicted wind speed was obtained. The suitability of the IF+GBM was tested using RMSE and r, the results shows a lower errors in some cases examined, though the model shows poor performance in one case, this could probably be as a result of low wind speed values in the region. Furthermore, a comparative with ARIMA model shows the proposed model is suitable to predict wind speed with high degree of accuracy. Further research work may consider how to improve the model to predict wind speed in the areas with very low wind speed values.

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