Prediction model of wind speed using hybrid artificial neural network based on Levenberg-Marquardt algorithm

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ABSTRACT

In this paper, a new method is developed to model the wind speed data that is considered as a function of seasonal wind variations. A hybrid artificial neural network (HANN) is investigated based on the Weibull distribution model. The presented HANN model predicts wind speed data with seasonal and chronological characteristics similar to real wind data. The design of the wind farm was implemented using MATLAB software. The suggested model has been applied and validated with wind data collected from the site of Tangier-MED in Morocco over two years, 2015 and 2016. The errors in terms of mean absolute percentage error MAPE and root mean square error RMSE are respectively 0.011 and 0.067 in 2015.

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1. INTRODUCTION

In the last two decades, the world has been increasingly turning to sustainable energy sources [1] such as solar [2]–[4] wind [5], [6] and waves to benefit from and to use in order to replace conventional fossil fuels. However, these sources are insufficient to meet the demands of the ever-growing population [7]. Unlike conventional generators, renewable energy generators can only produce energy when green energy resources are available. As a result, accurate prediction, control, and representation of renewable energy systems are critical [8] to ensuring a stable and continuous energy supply. The properly representation of probabilities, uncertainties, and fluctuating behaviors of the renewable energy systems allow them to be accurately optimized [9].

Wind energy is random and volatile, and its speed is the main parameter that influences wind power. Accurate wind speed prediction is beneficial to power system operation, security analysis, peak regulation, and energy saving. Therefore, accurate forecasting of wind speed is critical [10], [11]. In addition to its speed, wind is also characterized by its direction, and the time of occurrence. Wind energy is derived from natural wind flow depending on the force with which it moves or its speed. The successful profiteering of wind energy depends on the wind resources available in the area [12]. The economic viability of wind energy converters is determined by the wind conditions at a given location. Wind turbines require wind to be greater than 4 m/s so as to generate electricity [13]. Lower wind speeds can be sufficient for wind turbines. Most wind turbines, on the other hand, start to furl when the wind speed is between 12 and 15 m/s. It is difficult to obtain reliable data on wind speed specifically for the estimation of wind resources. Thus, specific wind speed models [14] are developed based on previously collected wind speed data records.

Several approaches to predicting wind speed have been investigated, and they are classified into the following four types; statistical, physical, artificial, and spatial correlation models. Statistical models, as opposed to physical models, are generally simpler and more suitable for small farms. In terms of wind speed prediction, hybrid models perform significantly better than simple models [15]. The majority of early research on the prediction of wind speed is based on physical or numerical mathematical models. This research suggests a hybrid model (a merge of a Weibull method and an artificial neural network).

2. MATERIALS AND METHOD

In this section, the proposed model for short-term wind speed prediction is described where the ANN technique and the Weibull model have been effectively integrated. The HANN model's goal is to improve the Weibull model's performance to a high level of accuracy. Variations in seasonal characteristics are taken into account in such hybrid methods.

2.1. Weibull distribution model: Wind speed modeling

The probability distribution [16] function of Weibull is given by (1).

$$f(v) = \left(\frac{k}{c}\right)\left(\frac{v}{c}\right)^{k-1} e^{-\left(\frac{v}{c}\right)^k} \tag{1}$$

Where $v(v \geq 0)$ is the wind speed, k (k> 0) and $c(c > 0)$ are the Weibull form and scale parameters.

By carefully configuring the shape and scale to meet the available experimental data, this distribution is used to represent wind speed. The more the Weibull distribution's scale parameter c is near to the average wind speed, the more the Weibull distribution is the best model. As indicated in (2), the Weibull cumulative additional function $F(v)$ calculates the likelihood that the speed will surpass the value v.

$$F(v) = e^{-\left(\frac{v}{c}\right)^k} \tag{2}$$

The cumulative function $F(v)$ for the wind speed allows the probability that the wind speed is $\leq v$. So, $F(v)$ is the integral of the PDF and given by (3).

$$P(v) = 1 - e^{-\left(\frac{v}{c}\right)^k} \tag{3}$$

To model the wind speed, the inverse transformation of the density of probability PDF is used. The inverse transformation of PDF is mostly used. Let (U) the random variable uniformly distributed between [0, 1] as expressed by (4).

$$U = F(v) = 1 - e^{-\left(\frac{v}{c}\right)^k} \tag{4}$$

Using the inverse transformation method, the wind speed v is demonstrated in (5).

$$v = c\left[-\ln(1 - U)^{\frac{1}{k}}\right] \tag{5}$$

Because each $W = (1 - U)$ is a random variable with a uniform distribution between [0, 1], then, we can write (5) in a simpler form as (6).

$$\mathrm{v} = \mathrm{c}\left[-\ln(\mathrm{W})^{\frac{1}{\mathrm{k}}}\right] \tag{6}$$

Finally, by using in (6) the wind speed v can be artificially generated.

Diverse numerical approaches are used to estimate the Weibull parameters [17]. In this work, the maximum likelihood method is used to estimate the shape parameters k and scale c. This approach is considered as a subset of the moment method, and its normal deviation and mean wind speed ($\bar{v}$) may be derived using (7) and (8) as shown below respectively.

$$k = \left(\frac{\sum_1^n (v_i)^k \ln(v_i)}{\sum_1^n (v_i)^k} - \frac{1}{n}\sum_1^n \ln(v_i)\right)^{-1} \quad (7)$$

$$c(k) = \left(\frac{1}{n}\sum_1^n (v_i)^k\right)^{1/k} = \left(\sum_{i=1}^n \frac{v_i^k}{n}\right)^{1/k} \quad (8)$$

Where v_i is the statistical wind speed (measured).

2.2. ANN model

The Weibull model's time series data are fed into the ANN model to anticipate the wind speed. In this study, the used wind data (speed and direction) per hour were collected from the Moroccan station. ANN is a computational tool inspired by the brain's central nervous system [18]. This tool is used to create a function based on various known inputs. The structure of the ANN model to predict the wind data [19]–[21] is shown in Figure 1.

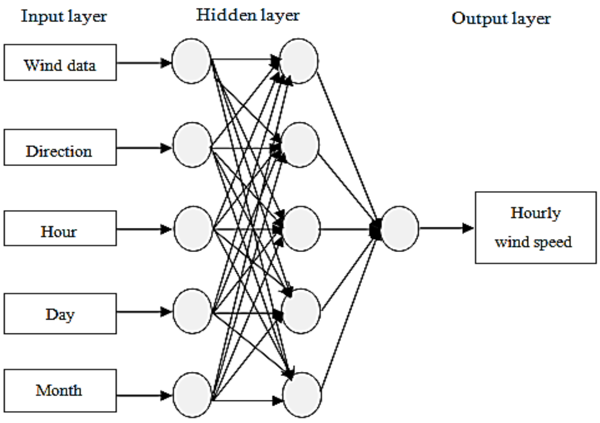

Figure 1. The structure of an ANN

The ANN fitting tool is used to forecast hourly data for various locations, and the statistical adjustment used in our case is based on the Levenberg–Marquardt algorithm [22], [23]. A two-layer feed-forward neural network serves as the fitting tool. The data are randomly split into 60% training, 20% testing, and 20% validation. Based on the error, the training data adjust the network weight. The validation data access network generalization and stop training when generalization no longer improves. The (9) yields the hidden layer neurons.

$$\mathrm{H_n} = \frac{\mathrm{I_n} + \mathrm{O_n}}{2} + \sqrt{\mathrm{S_n}} \quad (9)$$

Where $\mathrm{H_n}$ and $\mathrm{S_n}$ are the data samples number and the number of hidden layer neurons utilized in the ANN model, respectively, and $\mathrm{O_n}$ and $\mathrm{I_n}$ are the index of output and input parameters [24]. When generalization stops improving, as evidenced by rising in the root mean square error (RMSE) of the validation data, the training automatically terminates. Due to the various initialization of connection weights, repeated training sessions yield varying results.

2.3. Schema for integrated model

The HANN Levenberg–Marquardt algorithm is experienced in this model using collected wind speed data from a given location. The general methods involved in using the HANN model to simulate and predict wind speed data are illustrated in Figure 2. This model can be stated as:

- The Weibull parameters are fitted to generate a random hourly speed
- The ANN is used to increase the hourly data to match the features of the real data
- The prediction period is determined by the needed time period

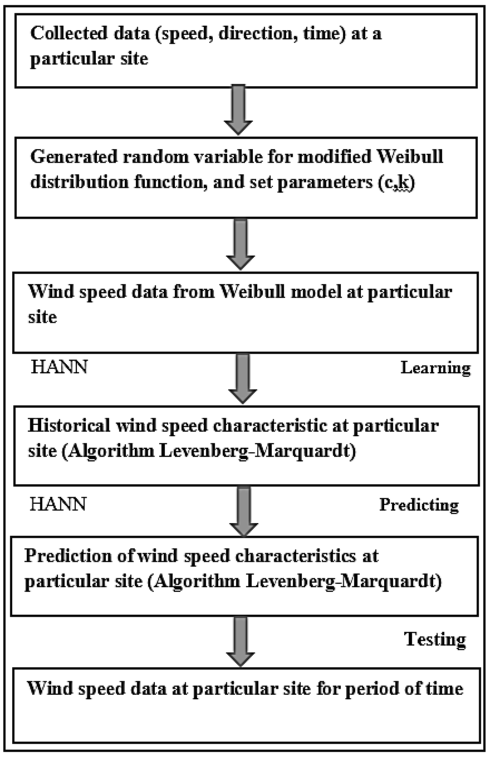

Figure 2. HANN model flowchart

2.4. Prediction error analysis

Two statistical errors, the mean absolute percentage error (MAPE) and root mean square error (RMSE MAPE), were used to evaluate the proposed HANN model [25], [26]. The MAPE measures the precision with which time series values in statistics, particularly trends, are fitted. The accuracy of wind speed prediction is determined by MAPE and described by (10):

$$\mathrm{MAPE} = \frac{1}{n}\sum_{k=1}^{n}\frac{y_i - y_k}{y_k} \qquad (10)$$

n: the total number of output and input pairs used in training
y_i : the hourly forecast wind speed
y_k : the hourly actual wind speed

A MAPE of 10% shows great prediction accuracy; a MAPE up to 20% suggests good prediction; a MAPE up to 50% indicates acceptable prediction; and a MAPE more than 50% indicates erroneous prediction. RMSE illustrates the effectiveness of the created ANN model in forecasting individual values; a big RMSE implies a significant departure between the predicted and real values.

3. DISCUSSION OF RESULTS

3.1. K, C parameter calculation

In this section, the wind speed estimation for the years 2015 and 2016 at the Tangier-Med port site using a Weibull distribution is presented. Therefore, the parameter ‘c’ was calculated using the data of the specific month in terms of the ‘k’ parameter. Table 1 illustrates the two calculated parameters Weibull (k, c) by the Maximum Likelihood method using the collected data in 2015 and 2016. From the Table 1, the Weibull c scale value is near to the real mean of speed. This examination recommends that the distribution of Weibull is the appropriate one and presents a very advantageous method for predicting wind energy than the classical models.

Table 1. Estimation of k and c parameters

Month	Year 2015		Year 2016	
	k	c	k	c
Jan	1.9001	11.7903	1.7221	11.9799
Feb	2.7283	15.7030	2.4316	16.4437
Mar	1.9461	10.3844	2.3323	11.9327
Apr	2.1220	11.6290	1.9107	10.6220
May	2.1759	11.4024	2.5633	12.2559
Jun	2.5592	11.4749	2.6474	12.2225
Jul	2.0991	9.42587	2.1294	11.7365
Aug	2.5971	10.7717	2.3778	12.7408
Sep	2.2609	10.5689	2.6430	10.8253
Oct	1.8794	7.8848	2.2580	10.6016
Nov	1.9544	11.2225	2.6517	11.0666
Dec	2.3319	9.5344	2.5329	10.4003
Mean	2.21	10.98	2.35	11.90

3.2. The prediction by the weibull model

The figures below show the simulation of the chronological data of the wind speed with c=10.98, k=2.21 (respectively c=11.90, k=2.35) for the collected wind data on the site in 2015 (respectively in 2016). Figures 3 and 4 (respectively Figures 5 and 6) show, respectively, the comparison between the real and simulated data of the Weibull model for six months and one-year of 2015 (respectively of 2016) in the studied site of Tangier-Med at a height of 10 m.

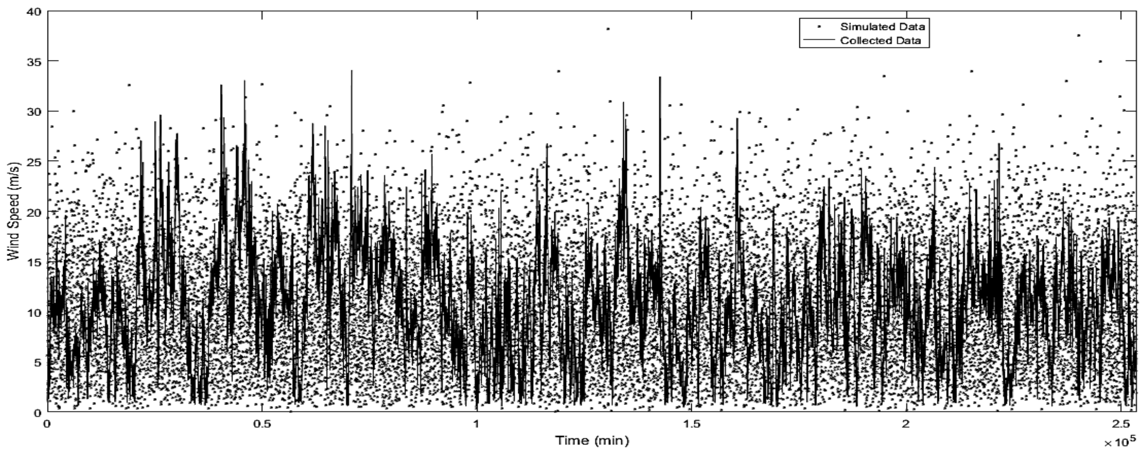

Figure 3. Wind speed comparison for six months 2015

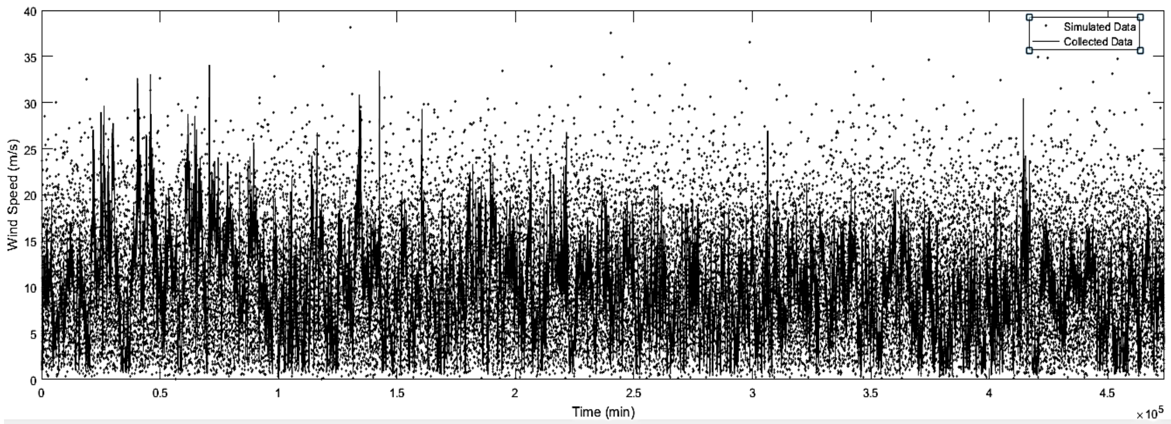

Figure 4. Wind speed comparison for one-year 2015

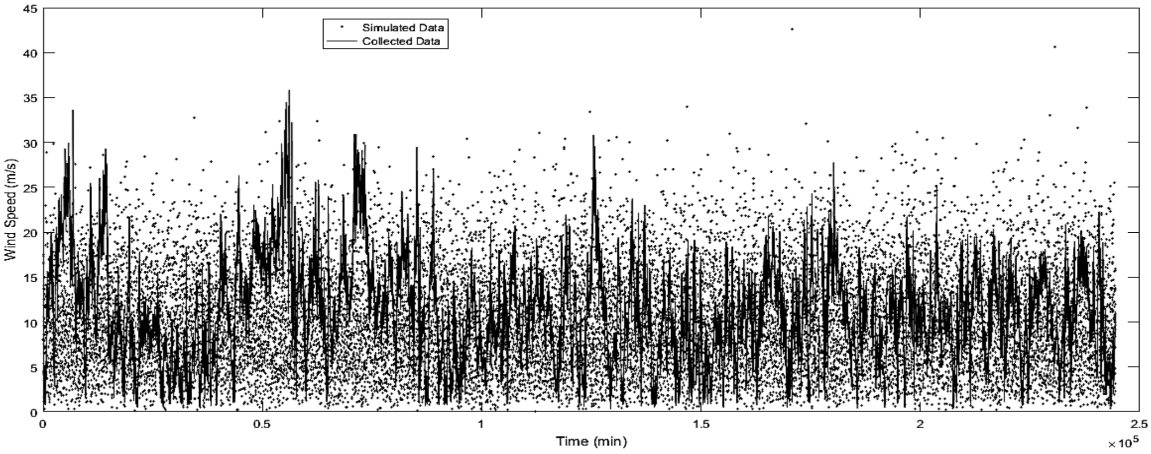

Figure 5. Wind speed comparison for six months of 2016

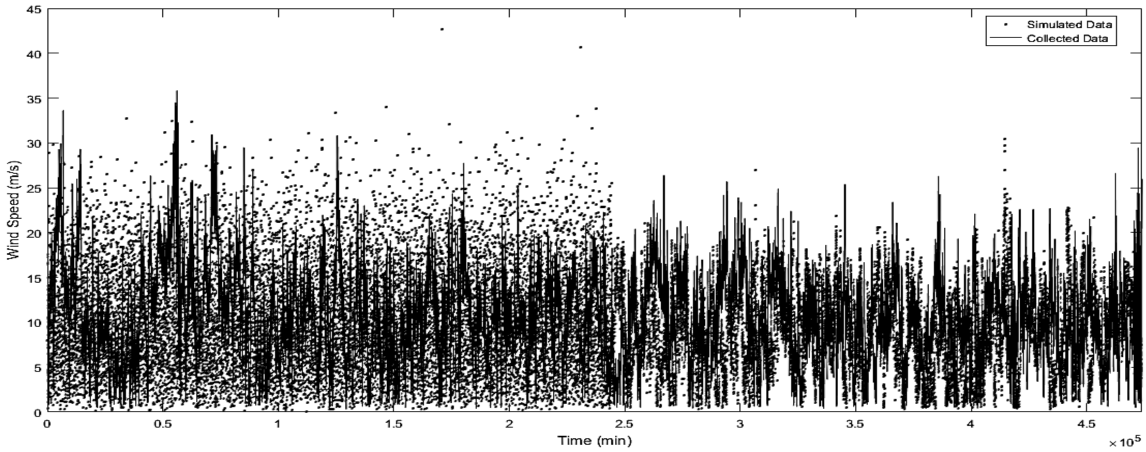

Figure 6. Wind speed comparison for one-year 2016

As illustrated, these speed data are different from the real ones, implying a low predictability. The difference between $\overline{v}$ and the 'c' shows that the Weibull model does not take into account seasonal variations in the calculations over the year. In order to eliminate inaccuracies in the wind speed data created from the Weibull model, basically for the highest wind speed seasons, a model of Hybrid artificial neural network is investigated to correct wind speed error.

3.3. Implementation of ANN and HANN models

In this part, we illustrate the implementation of the proposed ANN and HANN model to evaluate the wind data generated using Weibull distribution. Figures 7 and 8 (respectively Figures 9 and 10) show the comparison between the measured and simulated wind speed for two weeks and two months of the year on the site of the Tangier-Med port in 2015 (respectively in 2016) using the simplest ANN.

The collected data in 2015 are used as input for the predictive-only artificial neural network algorithm in the training and testing step. Finally, Figures 11 and 12 (respectively Figures 13 and 14) show the comparison results between the measured and simulated speed data for two weeks and two months in 2015, for the wind data on the site of the Tangier-Med port (north of Morocco), respectively in 2016 using HANN model.

The results illustrate that the studied method is suitable for predicting both hourly and daily wind series. The obtained results show that good predictions of wind speed can be made with the Weibull model and the artificial neural network model, respectively. However, the use of the hybrid artificial neural network model produces perfect and precise results.

The studied HANN is compared to the ANN model and the Weibull model. This comparison demonstrates that the HANN model exhibits lower RMSE and MAPE error for distinct horizons. The results were compared in terms of MAPE and RMSE for: Weibull, ANN and the HANN models, as presented in Table 2 .The values of MAPE and RMSE for two weeks, and two months of the year in 2015 and 2016, were 0.011, 0.067, 0.054, 0.201, 0.013, 0.077, 0.064, and 0.214, respectively. The proposed HANN model shows great prediction accuracy.

Table 2. Statistical errors for the Weibull, ANN and HANN models

Model	Year 2015 2 Weeks MAPE	Year 2015 2 Months RMSE	Year 2016 2 Weeks MAPE	Year 2016 2 Months RMSE
Weibull	0.851	1.430	1.335	2.281
ANN	0.022	0.186	0.094	0.354
HANN	0.011	0.067	0.054	0.201

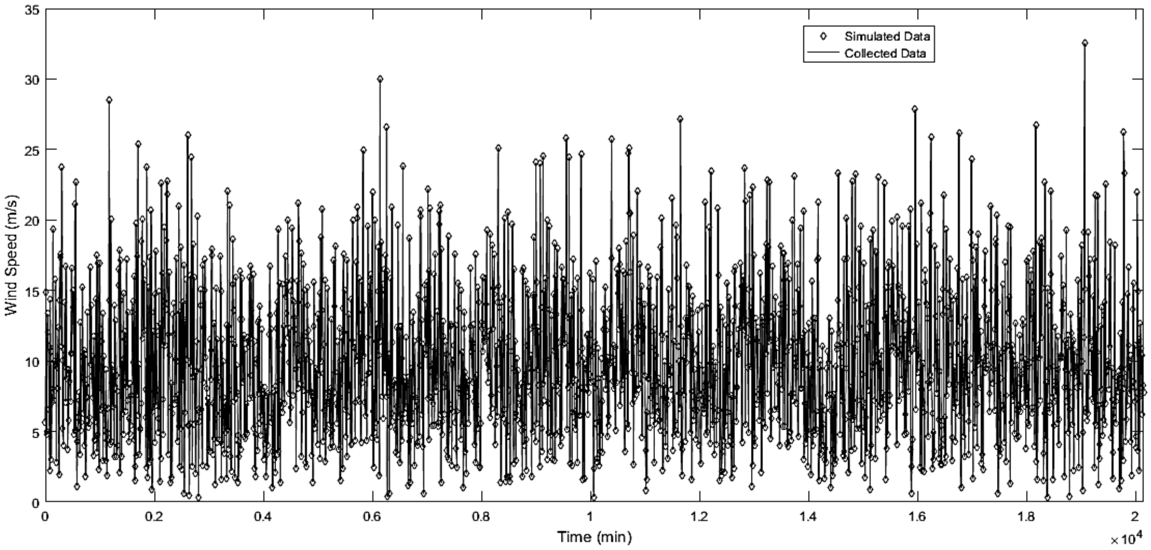

Figure 7. Wind speed comparison for two weeks 2015 using ANN

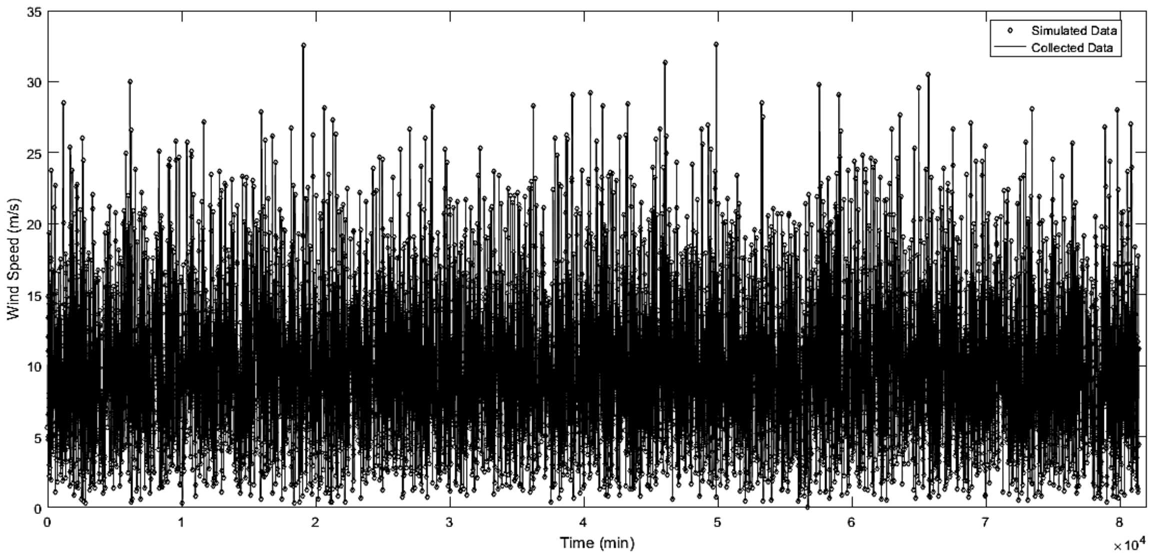

Figure 8. Wind speed comparison for two months 2015 using ANN

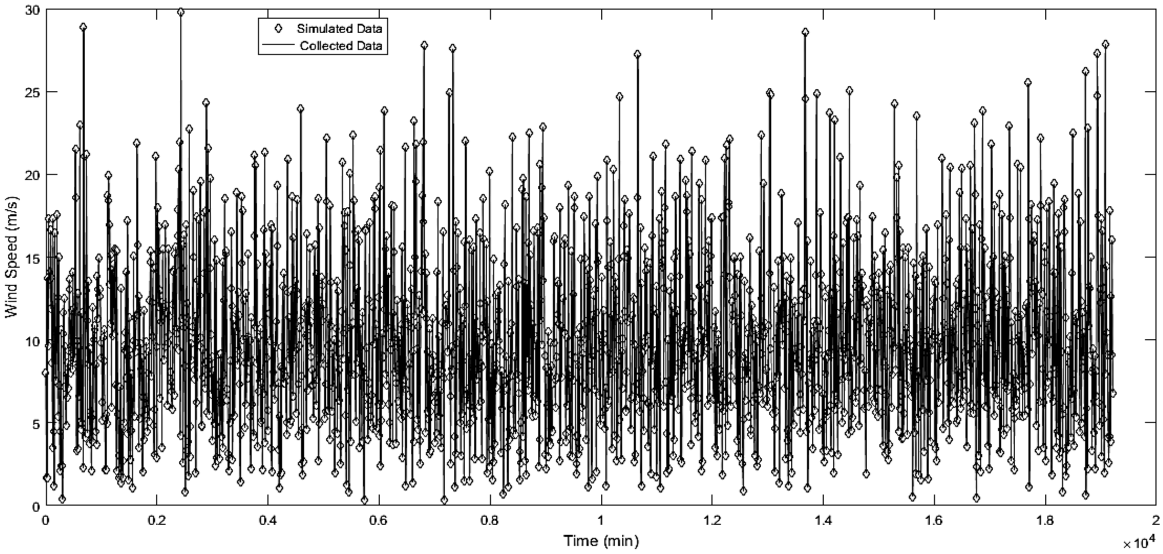

Figure 9. Wind speed comparison for two weeks 2016 using ANN

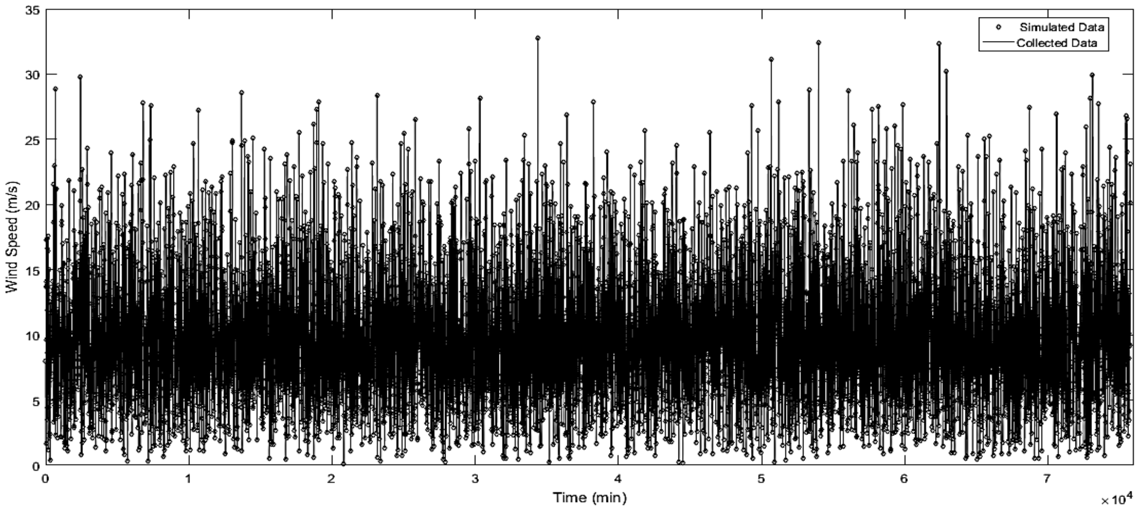

Figure 10. Wind speed comparison for two months 2016 using ANN

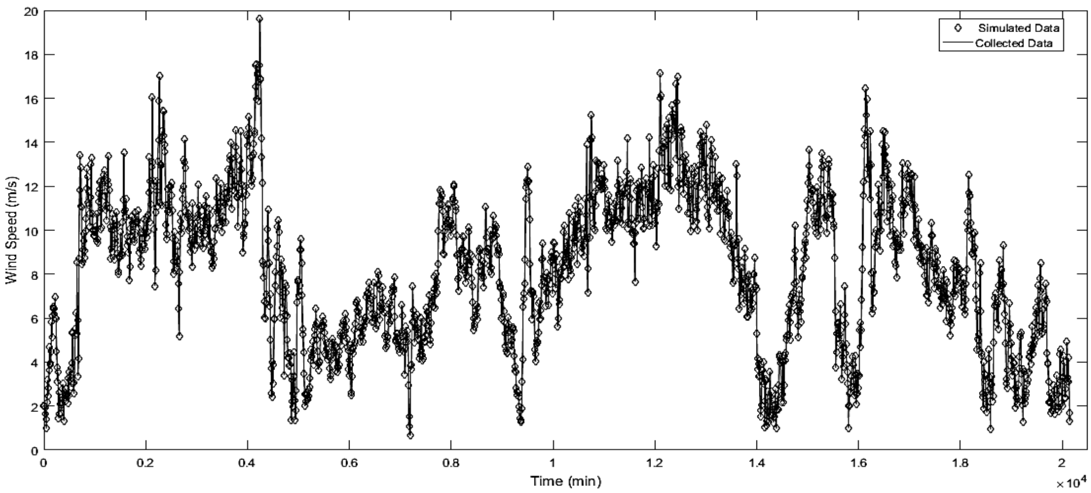

Figure 11. HANN validation using two weeks data in 2015

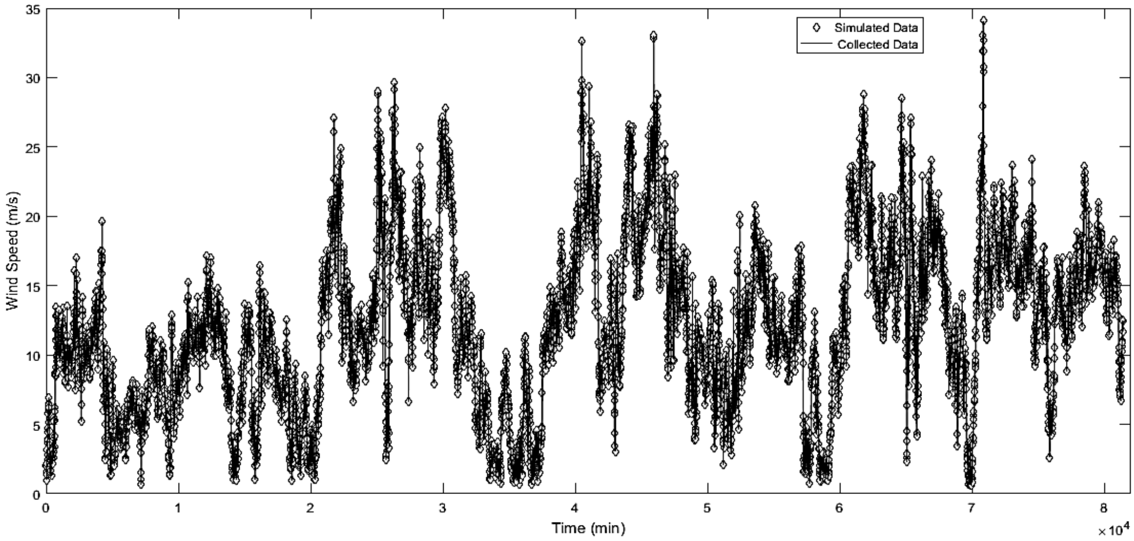

Figure 12. HANN validation using two months data in 2015

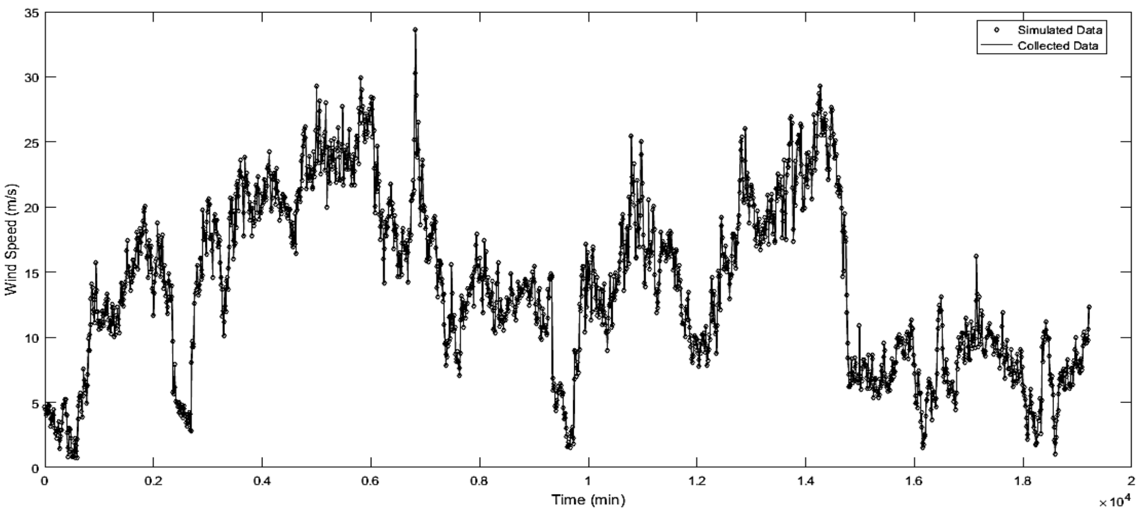

Figure 13. HANN validation using two weeks 2016

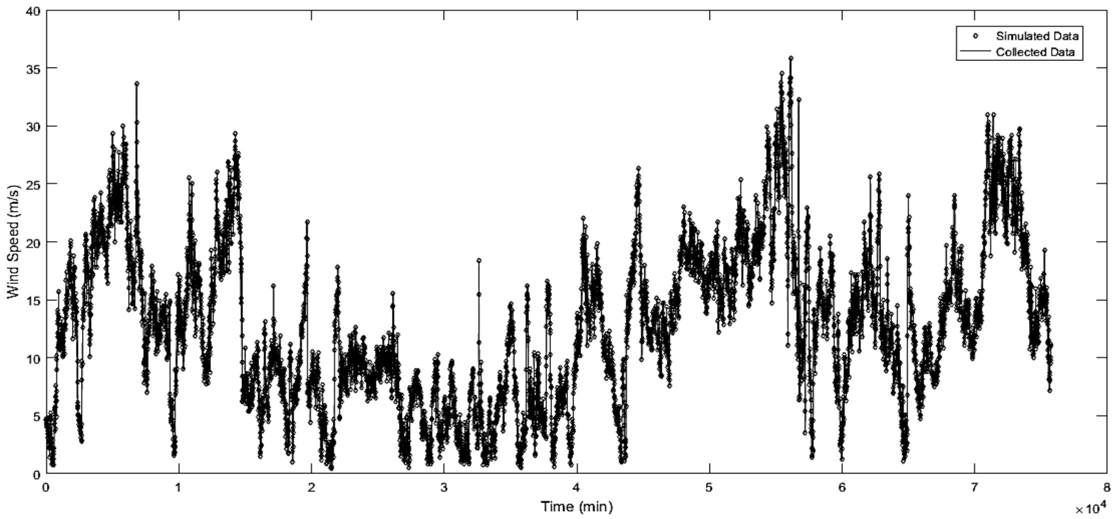

Figure 14. HANN validation using two months data in 2016

4. CONCLUSION

In the present study, a Hybrid-ANN method based on the Weibull distribution and ANN was developed. The model predicts the wind speed by taking into account the seasonal variations of the wind over a particular period of time, and the validation is achieved with the collected data at the Tangier-Med port in Morocco. The proposed Hybrid-ANN model is able to represent the fluctuating wind speed during distinct seasons of the year in different sites. The fundamental liaisons between wind speed and seasonal climatic variations are exploited. The predicted wind speed data are closely identical to the real wind data, and the errors are smaller than those produced using only the Weibull model

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