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WIND SPEED PREDICTION BASED ON TSUKAMOTO FUZZY LOGIC MODEL WITH HARMONY SEARCH

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ABSTRACT
In this paper, a Tsukamoto Fuzzy Model with Harmony Search is proposed and developed to predict wind speed. The data used in this study were obtained from a meteorological station unit of the International Institute of Tropical Agriculture (IITA) located at Tarauni, Kano State for a period of one year and used for the training and testing of the model. The Harmony search algorithm was applied to estimate the fuzzy parameters. The predicted values were compared with the observed wind speed and the effectiveness of the model was judged based on absolute and relative error. The maximum absolute and relative errors obtained in the proposed approach were 0. 52 and 0.11 respectively.
Keywords: *Wind speed, Wind power, Prediction, Harmony search, Tsukamato model, Fuzzy logic.*

INTRODUCTION
The speedy growth in human population and industrialization necessitate the need for clean energy. Scarcity of fossil fuels (experienced in the beginning and in the mid-seventies), environmental effects and release of pollutant materials, which may be harmful to humans (and other living organisms) and contribute to global warming, were all factors that turned the attention of the relevant stakeholders in searching for sustainable energy sources (Vazquez and Iglesias, 2016).

Renewable energy sources such as hydro, solar, wave, tidal, geothermal and wind have advantages of operating in standalone and connected modes. Wind energy as a resource is clean, freely available and naturally abundant. It has been well-recognized as one of the most promising energy sources (Lawan, Abidin, Chai, Baharun and Masri, 2015; Desideri, Proietti and Sdringola, 2009). Wind energy has been harnessed decades ago, for sailing ships and machine grinding. Recently it has become popular for electrical power generation.(Zhang, Su, Baeyens and Tan, 2014). The development of wind power technology has attained a certain level of development, for the fact that wind turbines are cost effective, which makes wind energy a major competitor of conventional sources. The percentage of wind energy share based on the energy mix around the globe is shown in Figure 1 ("GLOBAL WIND REPORT 2016 GWEC").

Prediction of wind speed has been carried out using mathematical and statistical models. (Kulkarni, Patil, Rama, and Sen, 2008). According to (Khatib, Mohamed, and Sopian, 2011), no realistic model either physical or mathematical could give a definitive solution.Because of the mentioned reasaons machine learning is found to be more attractive in recent times. Over the past few years, several studies were conducted based on machine learning to predict wind speed. Those studies can be catalogue into Artificial Neural Networks (ANN) and fuzzy logic (Akintunde, 2011). Different prediction horizons were suggested such as short-term, medium term and long-term wind speed forecast.

The reported work of (Lee, Park, Kim, Kim, and Lee, 2012) developed a wind speed prediction scheme using modified harmony search and neural networks. It was found that machine learning wind speed prediction models give an utmost, way of predicting wind speed in the areas where measured wind speed is not observed. In this study, a model to predict wind speed for wind energy potential assessment is developed using a new improved methodology, which combines harmony search algorithm with a fuzzy inference systembased on Tsukamoto model. Analyses were carried out to validate the predictionaccuracy, using experimental data observed in the study area.

Fuzzy Inference System Tsukamato Model
In general, a fuzzy inference system consists of four components: fuzzification, fuzzy rule base, fuzzy inference engine and defuzzification (Sideratos and Hatziargyriou, 2012). In fuzzification, each input is converted into a fuzzy variable. A membership function (MF) maps each input set to a membership value between 0 to 1. Fuzzy MFs can be written in different forms, such as triangle, trapezoid, Gaussian or sigmoid functions. The fuzzy rule base component consists of all possible fuzzy relations between inputs and outputs, which are expressed in the form of the IF-THEN format. Three types of models in fuzzy inference system are the Mamdani model, the TSK model and the Tsukamoto model (Hervás-Martínez, Salcedo-Sanz, Gutiérrez, Ortiz-García and Prieto, 2011). The fuzzy inference engine component considers all the fuzzy rules in the fuzzy rule base and transforms a set of inputs to corresponding outputs by minimization (min) or product (prod) operators. Lastly, defuzzification converts fuzzy outputs from fuzzy inference system to a number.

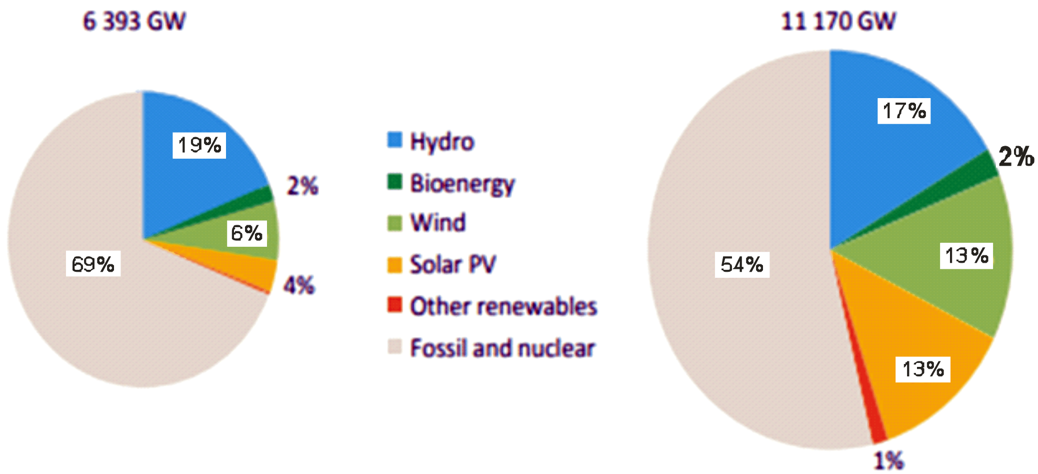

Figure 1: Wind share based on world energy mix change 2013-2017 (“GLOBAL WIND REPORT 2016 | GWEC”)

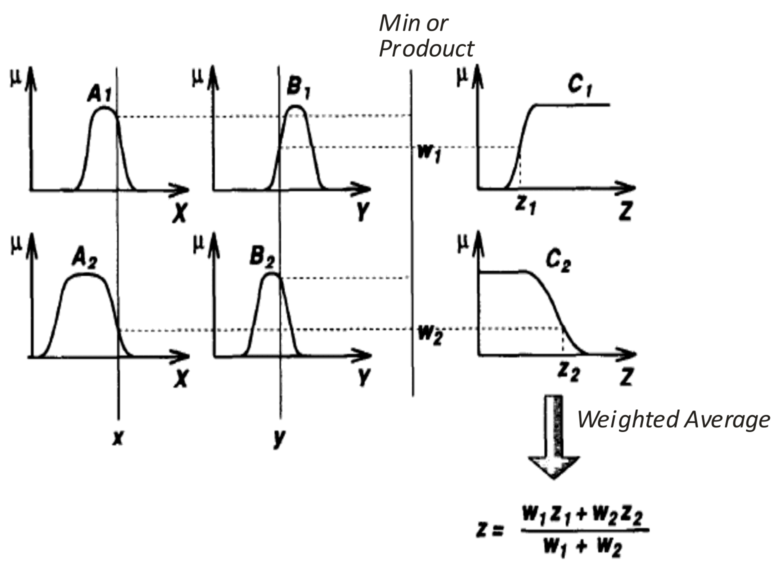

Figure 2: The Tsukamoto fuzzy model (Sari, Wahyunggoro and Fauziati, 2016)

In this study, Tsukamoto model was used, because of its ability to solve nonlinear ill-defined problems. Each input is converted into several Gaussian functions. In a fuzzy inference engine, product, operator was used to transform input to output. In Tsukamoto model, the fuzzy MF for the outputs must be a monotonic function, which maps the firing strength of each rule to a unique output value (Zeng and Qiao, 2011). The overall output equals to the weighted average of each rule’s output. The reasoning procedure for a two-input two-rule system is illustrated in Figure 2 (Haque, Mandal, Meng and Kaye, 2012).

Harmony Search Algorithm

Harmony search (HS) is an optimization algorithm which is inspired by music improvisation. This algorithm seeks the ideal state as determined by objective function evaluation by mimicking musical improvisation process by musicians. In a musical practice, musicians always try to find a better harmony (Uçkun Kiran, Trzcinski, Ng and Liu, 2014). If the musicians find a good harmony, they will keep it in their memory. The pitches of the instruments are changed after each practice. After some trials, if they manage to find a better harmony, they will replace the previous record with the new one.

It is believed that the best harmony could be accomplished after numerous trials (Tiang and Ishak, 2012). The steps used for the harmony search algorithm development are shown in Figure 3.

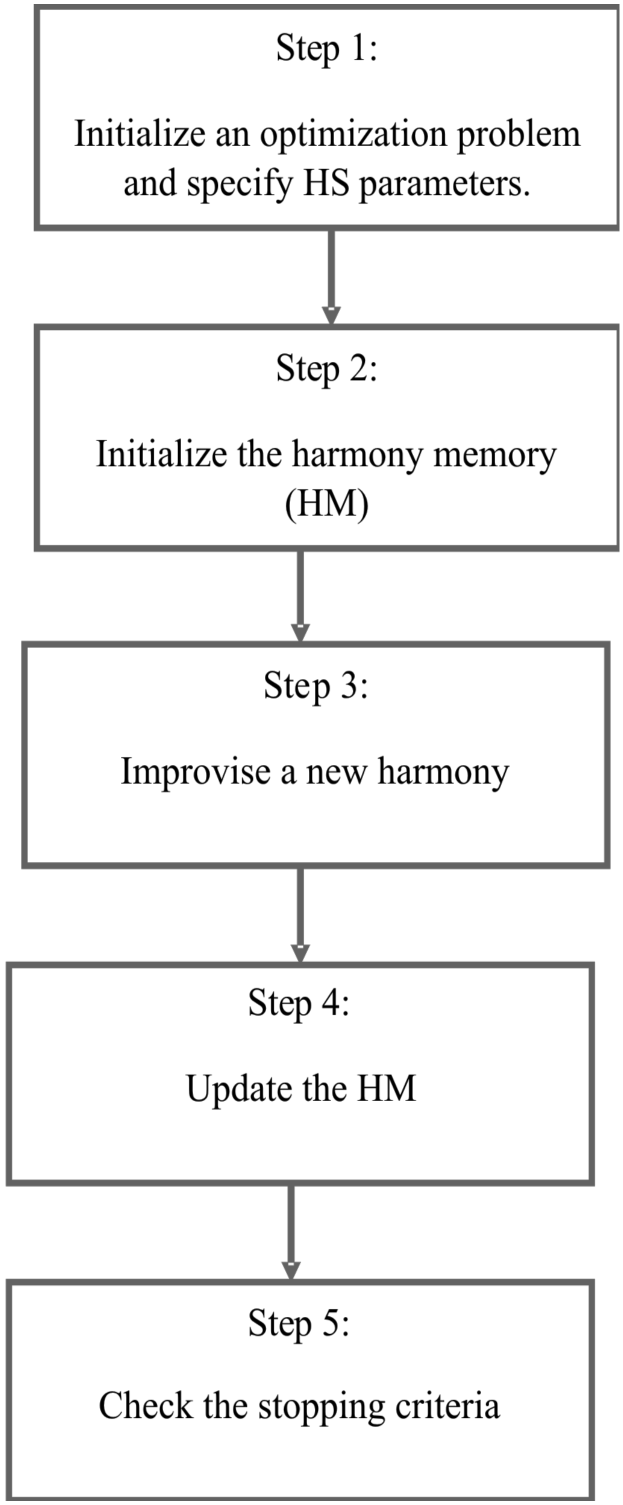

Figure 3: Harmony Search Alg orithm

In step 1, an optimization problem or objective function is determined. At the same time, HS parameters such as harmony memory size (HMS), harmony memory considering the rate (HMCR), pitch adjusting rate (PAR), number of improvisations (NI) or the stopping criteria must also be specified. In this study, the optimization problem is to minimize the objective function, which is the total squared error value between predicted outputs from the model with output from data sets. HMS values are taken as 20-100, HMCR values of 0.7-0.95 and PAR values of 0.2-0.7. In order to obtain a smooth function. In step 2, a new HM matrix is generated based on HM consideration, pitch adjustment and random generation. In step 3, if the new harmony is better than the worst harmony in HM, the new harmony will be included in the HM and the existing worst harmony is excluded from HM. Steps 3 and 4 are repeated until the termination criteria is satisfied.

METHODS

In this study, wind speed prediction model was developed in three steps: data collection, Fuzzy Tsukamoto and harmony search modeling, and prediction of wind speed. The model was developedusing MATLAB/Simulink 7.10.0 (R2012a) platform, 4 GB RAM and Intel (R) core (TM) i5. Details of the methodology are given below.

Data collection

The meteorological data (Wind speed, sunshine hours, maximum and minimum temperature, Rainfall, Relative humidity, and evaporation) used in this study were obtained from Ahmadu Bello University, Zaria Agricultural Research Institute, situated at Tarauni, Kano State for a period of 1 year (2015-2016). The wind speed was collected at a height of 5 meters using a rotating cup anemometer and wind vane. The data collected at an update rate of every 2 seconds, and averaged every ten minutes. The ten minute average wind speeds were additionally averaged over a period of one hour to obtain the hourly average wind speed. The latitude, longitude, altitude, observation time frame and years of measurements are shown in Table 1.

Table 1: Study area description

Station Name	Latitude (N)	Longitude (E)	Altitude (m) above the ground level	Data Duration
ABU IITA, Kano	11.9587°	8.5446°	2.7	2015-2016

The data values for wind speed in this study ranged from 3.67 m/s to 5.34 m/s. The minimum and maximum temperature ranged from 29.50˚C to 40.40˚C. Table 2 shows the range of each component in the database. A total of 365 data is obtained, and 70% of the data were used in training (255 days) while the remaining 30% (110 days) was used in testing the model. Summary of the data is shown in Table 2.

Fuzzy tsukamoto and harmony search modeling

The Tsukamoto model in this study has six (6) inputs and one (1) output system. The inputs are temperature, rainfall, humidity, evaporation, sunshine hours and month. Each input is converted into 3 Gaussian MFs. Each Gaussian MF has two parameters, c and σ, where c represents the MF's centre and σ is the MF's width ("Wind in power," 2016). The Equation for a Gaussian MF is given in (1). The number of fuzzy rules is determined using grid partition.

$$\text{Gaussian} = \mu \quad xA^i(x) = \exp\left[-\frac{(c_i - x)^2}{2\delta_i^2} \right] \qquad (1)$$

where c_i and σ_i are the centre and width of the *ith* fuzzy set A^i , respectively.

Table 2: Ranges of components of data sets

Parameter	Minimum	Maximum	Average
Maximum Temperature ˚C	29.50	40.40	33.93
Minimum Temperature ˚C	11.90	25.40	20.03
Rainfall mm	0.00	646.90	147.89
Humidity %	21.00	82.00	48.50
Evaporation ml	2.30	12.10	7.05
Sunshine (H) Hours	6.70	9.30	7.76
Wind Speed m/s	3.67	5.34	4.45

While, the harmonic data is generated using a quadratic function as given in Equation (2);

$$y(x) = x_1^2 + x_2^2 \tag{2}$$

The output of the system are wind speed and wind direction. A linear MF was used for the outp. Each output has two parameters, a and b, where a is the value on the linear line when the MF is 0 while b is the value when the MF is 1.All fuzzy parameters were determined using harmony search. In the harmony search model, the maximum and minimum values for each fuzzy parameter (as shown in Table 3) were foundusing the training dataset. The initial values used for HS parameters are shown in Table 3. A few trials using different HS parameters were carried out. The fuzzy parameters were taken as the values of the HS model which gave the least squared error value between predicted outputs from the model and the training dataset.

Table 3: Initial values of harmony search algorithm parameters

Parameter	Initial value
Harmony memory size (HMS)	10
Harmony memory considering the rate (HMCR)	0.90
Pitch adjusting rate (PAR)	0.2
Number of improvisations (NI)	10,000

All fuzzy parameters determined from the Tsukamoto fuzzy and harmony search models were used to predict the output for wind speed testing dataset. The predicted outputs from the model are compared with the outputs from testing dataset.

RESULTS AND DISCUSSION

In this section, the usefulness of our proposed approach will be demonstrated. We attempt to construct a two-input Fuzzy harmony search (FHS) model in such that it is close to (2). In this paper, 95 pairs of data are randomly generated using (2). Noise is then added to the 95 pairs of data. Adding noise results in non-monotone dataset. In our simulation, $w = 100$, refer to (2). HS is adopted to search for a set θwith settings as follows; harmony memory size (HMS) = 30, harmony consideration rate (HMCR) = 0.90, and pitch adjusting rate (PAR) = 0.20. The number of maximum evaluations (iteration) was set to 10,000.

Figure 4 shows the HS objective function versus the number of generations. The result shows that with 10,000 iterations the total least square error (LSE) found is equal to 3.135.

Figures 5 and 6 show the surface plot of the HS objective function tested with ($w = 100$) and without ($w = 0$) Monotone Index (MI) respectively. In Figure 2, a monotone FIS model is obtained. It shows that even with non-monotone data set, a monotone surface curve can be obtained with MI as the constraint. In Figure 3, without MI, a non-monotone surface curve is obtained.

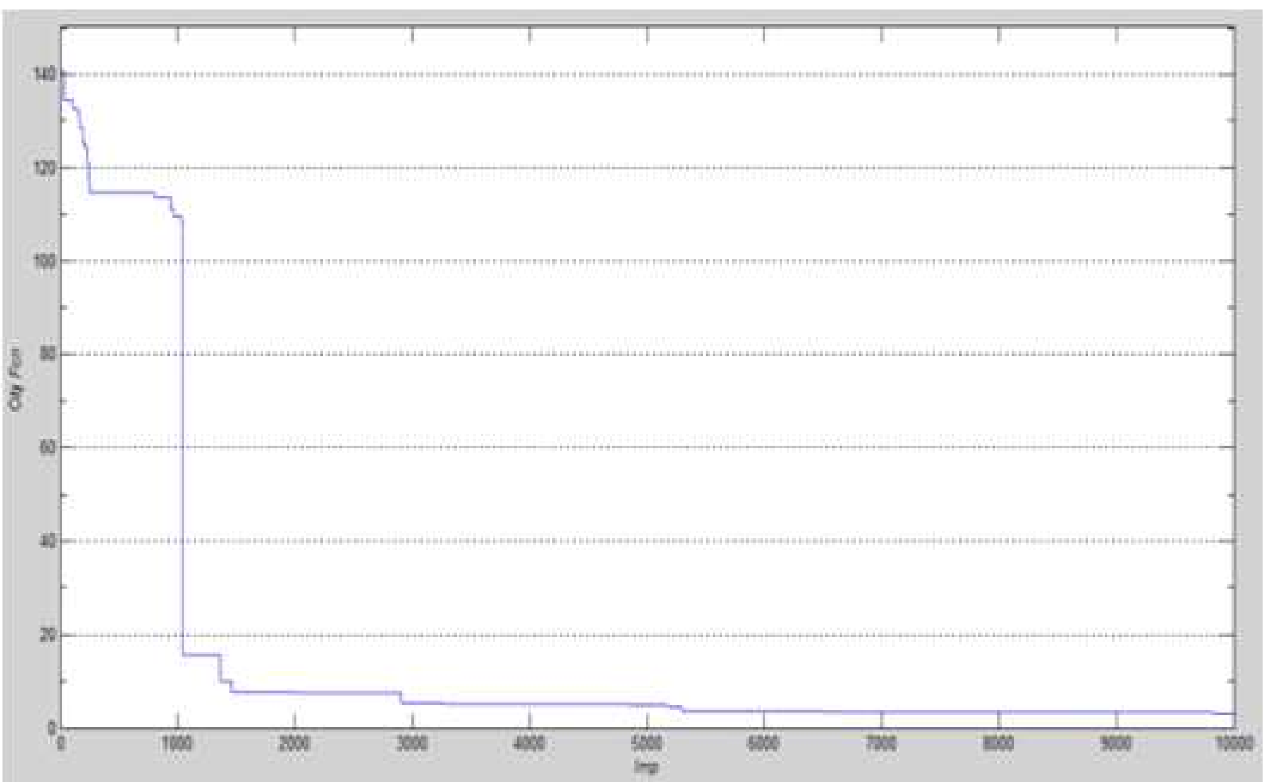

Figure 4: HS objective function versus the number of generations

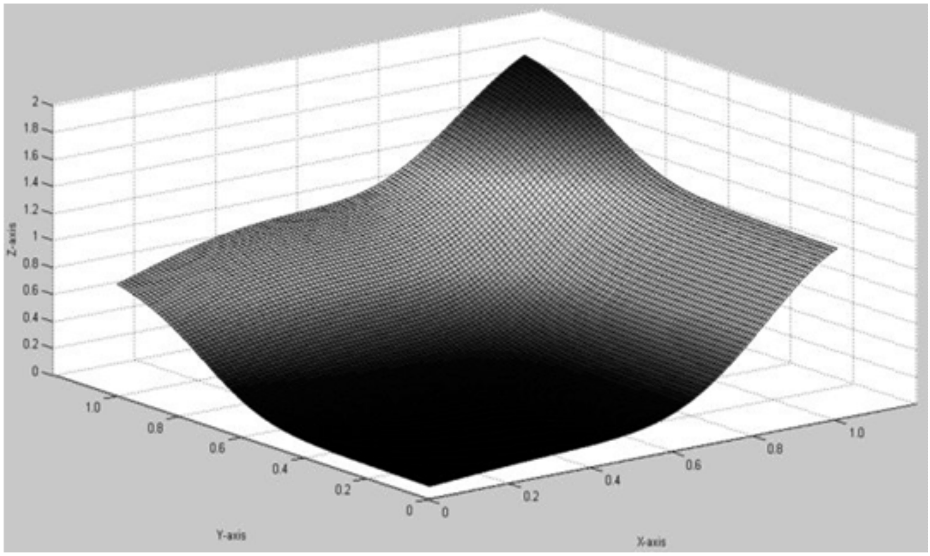

Figure 5: HS objective function versus the number of generations

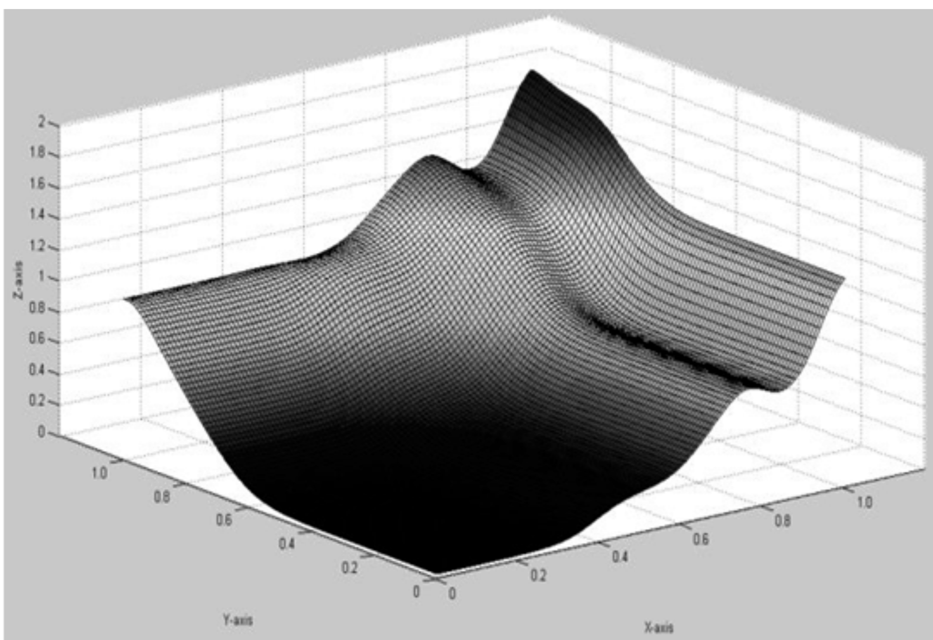

Figure 6: Noisy data tested without MI as a constraint

The target output is the experimental monthly wind speed measured at the monitoring station; the observed data were used as testing dataset. The testing results are shown in Table 4.

The maximum relative error found is 0.11%. This value shows that the results from the model are reasonably good, considering that the data sets are gathered from a reliable source. Furthermore, the maximum relative error in this study is quite close to a study by one study (Yan, Qian, Sharif and Tipper, 2013) which shows a maximum relative error of 0.12%.

CONCLUSIONS

In this paper, an improved methodology for wind speed prediction was demosrated. The model was designed based on the Tsukamoto fuzzy logic model with harmony search. The model was designed, simulated and analyzed using observed wind speed data. The suitability of the suggested method was judged by means of comparison between the predicted wind speed and ob served wind speed, the results show the suitability of using this method to wind speed prediction.

Table 4: Comparison between predicted and target wind speed

Month	Target wind speed (m/s)	Output of model wind speed (m/s)	Absolute error	Relative error (%)
Jan	4.70	4.82	-0.12	-0.02
Feb	4.60	4.75	-0.15	-0.03
Mar	3.90	3.67	0.23	0.06
Apr	3.70	3.59	0.11	0.03
May	3.70	3.59	0.11	0.03
Jun	4.80	5.34	-0.54	-0.10
Jul	5.30	4.78	0.52	0.11
Aug	5.00	5.09	-0.09	-0.02
Sep	4.70	5.09	-0.39	-0.08
Oct	3.70	3.89	-0.19	-0.05
Nov	4.80	5.08	-0.28	-0.06
Dec	4.30	5.32	-1.02	-0.19

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