Energy and Environment Research; Vol. 12, No. 2; 2022
ISSN 1927-0569 E-ISSN 1927-0577
Published by Canadian Center of Science and Education

Wind Speed Forecasting Using Machine Learning Approach Based on Meteorological Data-A Case Study

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Received: May 25, 2020 Accepted: May 13, 2022 Online Published: July 14, 2022

doi:10.5539/eer.v12n2p11 URL: https://doi.org/10.5539/eer.v12n2p11

Abstract

This paper presents a forecasting method to anticipate wind speed accurately. This method is applied to an energy production site using an artificial intelligence method based on machine learning. The accuracy of this method is higher compared to other existing methods in the literature for time series analysis such as artificial neural networks and the complexity of wind speed prediction models without loss of information content. We tested several thousand data between 1985 and 2018 in the city of Basel, a city in northwestern Switzerland. We have used the MATLAB Software for this modeling. The study demonstrates that the use of statistical models based on machine learning is relevant to predict of speed and direction of the wind in power generation systems from meteorological data. The results obtained are presented and discussed.

Keywords: wind speed forecasting, wind energy, machine learning, artificial neural network, meteorological data of basel in Switzerland, airfoils blade profile, NACA profile

1. Introduction

Wind energy is a clean energy, which is in-exhaustive and infinite in nature. The major problem in this energy is the prediction of the speed and direction of the wind over an extended period of time. Forecasts and detection of speed and direction of wind in power generation systems in their probabilistic form are a necessary input to decision-making problems in power systems operations in a smart grid context (Tastu et al. 2014). Some research has demonstrated using statistical methods over physical methods. Statistical prediction methods (SPM) can use historical values of wind speed. SPM can be classified into two main approaches: 1) time-series models (such as autoregressive and moving average models) and 2) soft computing models (such as artificial neural networks (ANNs), fuzzy logic). Recent publications show that genetic algorithms (GAs), support vector machines (SVMs), and Kalman filtering (KF) models can be used in order to reduce prediction errors.

Several studies have been carried out on wind speed prediction, among others: A hybrid intelligent algorithm (Li and Shi, 2010), ANN models with acceptable accuracy (mean absolute percent error <10% and correlation <1 m/s) (Lee, 2017), a wind speed forecasting using time series analysis methods (Zhang et al. 2017), a probabilistic wind power forecasting method using quantile regression method (Noorollahi et al. 2016), a short-term wind speed prediction by linear and nonlinear autoregressive models(Bremnes, 2002), KF for short-term predictions(Bremnes, 2006),, or probabilistic wind power forecasting with consideration of geographically distributed information(Nielsen et al. 2005). Each method has certain limitations such as efficiency, accuracy, reliability and speed (Lau, 2011).

2. Analysis of Basel Area

We tested and analyzed for 35 years (from 1983 to 2018) the data of the wind speed of Basel. Basel is a city in northwestern Switzerland. In Figure 1 shows that it is a city with strong winds especially in winter. Then we applied our method based on these data in order to find the least error in terms of forecasting of wind speed (Hu, 2016). Wind speed prediction is extremely important for electricity production, energy storage, energy management, commitment decision and wind farms studies. Table 1 shows the different methods for different application areas of the aforementioned data analysis methods.

Table 1. Applications of data analysis methods for different application purposes (Damousis, 2001)

Methods	Applications				
	Clustering	Demand Response	Energy Production Optimization	Energy Pricing	Monitoring and Diagnostics
Linear Regression		√	√	√	
Support Vector Machine (SVM)		√	√	√	√
Neural Networks	√	√	√	√	√
K-Means	√				
Kalman filter		√	√	√	
Gaussian Process	√	√	√	√	
Principal Component Analysis (PCA) / Independent Component Analysis (ICA) / Nonnegative Matrix Factorization (NMF)	√				
Learning Vector Quantization (LVQ)	√				

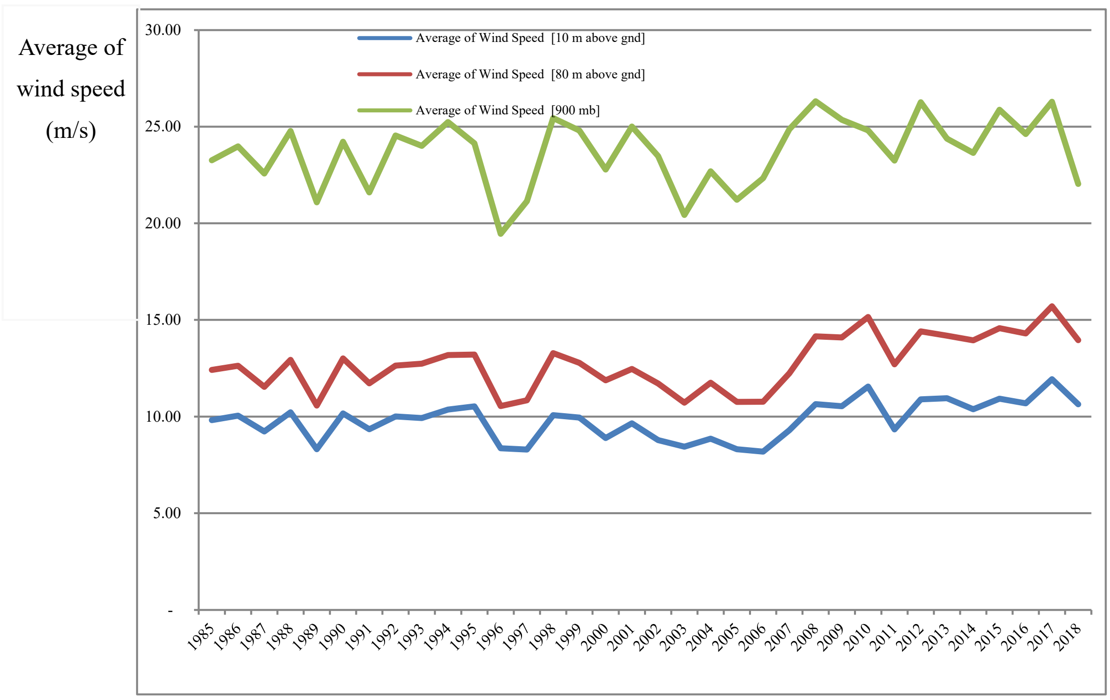

Figure 1. This is the Wind and weather statistics for the city of Basel, in north-western Switzerland. The wind statistics are based on real observations from the weather station at Basel

3. Wind Speed Distribution and Airfoils Blade Profile

Two important elements affect the performance of wind turbines. These elements are respectively: the profiles of the blades and the wind speed (Jursa and Rohring, 2008). Several mathematical models have been used to study wind data. To describe the statistical distribution of wind speed, various probability functions can be suitable for wind regimes. The distribution of Weibull allows having a good approximation of the distribution of the wind speed on a wind farm.

The Weibull probability density function is given by:

$$P(U) = \left(\frac{k}{c}\right)\left(\frac{U}{c}\right)^{k-1} \exp\left[-\left(\frac{U}{c}\right)^{k}\right] \tag{1}$$

Determination of the Weibull probability density function requires knowledge of two parameters: k, shape factor and c, scale factor. Moreover, U is the wind speed categories in m /s and e is Euler's number.

To simplify the calculation of the Weibull distribution in onshore installation, we can put k (shape factor) into three categories:

k = 2 for installation on earth

k = 3 for installations on the coasts

k = 4 for island facilities

Figure 2 shows the percentage of each category of wind speed on a wind farm. These curves show a comparison between a forecasting method of wind speed using the Weibull method and the practical results. We have compared the Weibull probability with measures for a wind category between 0 and 19 m/s. Theses resultants show that the higher percentage is intended for wind speed between 6 and 7 m/s about 14.15%, shown in Figure 2. This is an acceptable percentage for onshore wind turbines with three blades.

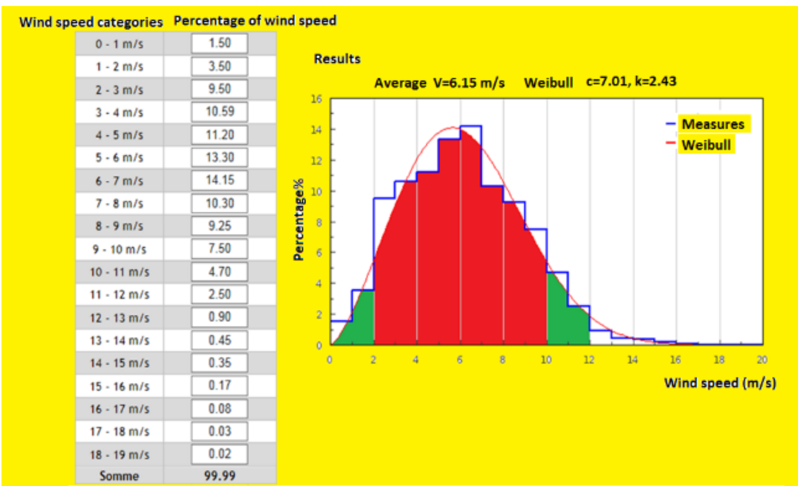

Figure 2. A comparison between the Weilbull distribution method and the practical results

Wind speed forecasting is an important element in a wind farm. Another major importance element is the airfoil profiles. The airfoil is the most important and basic characteristic of a wind turbine blade in the design of turbine rotors that will allow to operate with maximum aerodynamic performance (Liu et al. 2014). The wind turbine starts at cut-in speeds, generally around 3.5 m/s and shuts off the turbine at very high wind speeds over 25 m/s (cut-out speed), to protect the device (Chen and Agarwal, 2013). The correct operating range for a 3-blade onshore wind turbine is between 5 and 20 m/s.

Airfoil design for wind turbines, has become a fundamental issue. Airfoils created for airplanes are occasionally used in wind turbines (Ronit et al. 2012). There are several airfoils in wind turbines using the NACA catalog. Airfoils play an important role in the recovery of wind kinetic energy. Figure 3 shows a profile of NACA63-215 for horizontal axis wind turbine (HAWT) facing into the wind. In the characteristics of the blades, one of the important objectives is to decrease the value Cd (minimum drag coefficient and/or maximum lift coefficient Cl), as shown in Figure 4.

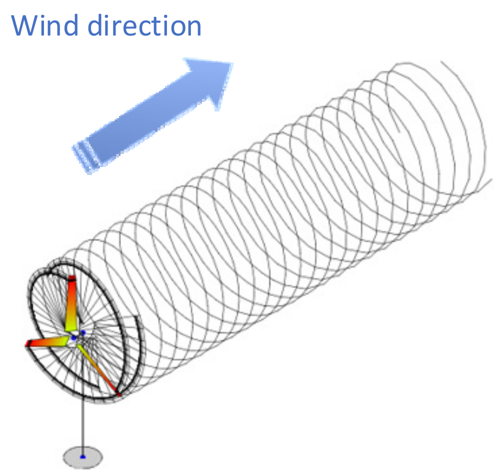

Figure 3. A 3-blade model using NACA63-215 for a wind turbine facing into the wind (3D modeling)

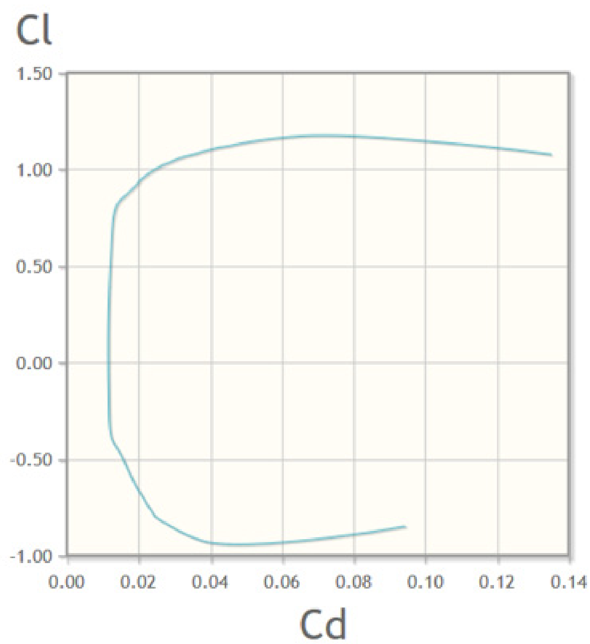

Figure 4. Curve of lift coefficient (Cl) and drag coefficient (Cd) for NACA 63-215 airfoil profile

In the literature, there are several methods of estimating parameters used in the distribution of Weibull. In this paper, analytical and empirical methods are used to find k and c, such as Justus (eq. 3) and Lysen (eq. 4) formulas demonstrated in the following form (Yahyaoui and Cantero, 2018) (George, 2014):

$$\sigma_u = \sqrt{\frac{\sum_{i=1}^{N} (U_i - \overline{U})^2}{N - 1}} \tag{2}$$

$$k = \left(\frac{\sigma_U}{\overline{U}}\right)^{-1.086}, \qquad \frac{c}{\overline{U}} = \frac{k^{2.6674}}{0.184 + 0.816k^{2.73855}} \tag{3}$$

$$\frac{c}{\overline{U}} = \left(0.568 + \frac{0.433}{k}\right)^{\frac{1}{k}} \tag{4}$$

where σ_U and U_i, $\overline{U}$ represent the Standard deviation and mean wind speed, respectively. Standard deviation also is defined through the value of k (Arslan et al. 2014):

$$\sigma_U = \overline{U}\sqrt{\left(\frac{\Gamma(1+2/k)}{\Gamma^2(1+1/k)} - 1\right)} \tag{5}$$

The energy pattern factor, K_e, whose application is in turbine aerodynamic design, can be defined as the total amount of power available in the wind divided by the power calculated from cubing the average wind speed is given by (Arslan et al. 2014) (Chang and Tian, 2011):

$$K_e = \frac{1}{N\overline{U}^3}\sum_{i=1}^{N} U_i^{\,3} = \frac{\overline{U^3}}{(\overline{U})^3} = \frac{\Gamma(1+3/K)}{\Gamma^3(1+1/K)} \tag{6}$$

Table 2 shows the average of wind speed (yearly) at different altitudes between 1985 and 2018.

The most important component of a wind turbine rotor is the design of airfoils. It is an important element that produces the forces that make the turbine rotate and to capture the kinetic energy of the wind. Two types of force are applied on each blade. The forces are called the lift (F_l) and drag (F_d). The parameters of utmost importance are the coefficients of lift (C_l) and drag (Cd) as shown below.

$$C_d = \frac{F_d/l}{\frac{1}{2}\rho W^2 c} \tag{7}$$

$$C_l = \frac{F_l/l}{\frac{1}{2}\rho W^2 c} \tag{8}$$

where:

ρ = density of air

W = velocity of undisturbed air flow

l = airfoil span

c =airfoil chord length

The NACA 63-215 is a 15% thick airfoil with a slight camber.

Table 2. Average of Wind Speed of 10m above ground, 80 m above of ground and 900mb

Date	Average of Wind Speed [10 m above gnd]	Average of Wind Speed [80 m above gnd]	Average of Wind Speed [900 mb]
1985	9.82	12.41	23.26
1986	10.05	12.63	23.98
1987	9.23	11.54	22.57
1988	10.22	12.94	24.78
1989	8.31	10.57	21.08
1990	10.17	13.01	24.22
1991	9.35	11.72	21.59
1992	10.00	12.64	24.54
1993	9.93	12.74	24.00
1994	10.36	13.18	25.24
1995	10.53	13.21	24.14
1996	8.36	10.54	19.46
1997	8.30	10.84	21.14
1998	10.07	13.28	25.44
1999	9.95	12.78	24.80
2000	8.89	11.87	22.78
2001	9.65	12.46	25.01
2002	8.78	11.71	23.48
2003	8.44	10.72	20.43
2004	8.86	11.75	22.69
2005	8.31	10.76	21.22
2006	8.19	10.77	22.33
2007	9.30	12.24	24.86
2008	10.64	14.15	26.31
2009	10.53	14.09	25.35
2010	11.55	15.15	24.80
2011	9.33	12.70	23.25
2012	10.89	14.41	26.26
2013	10.95	14.18	24.38
2014	10.38	13.94	23.64
2015	10.92	14.58	25.87
2016	10.68	14.30	24.62
2017	11.94	15.71	26.29
2018	10.64	13.95	22.03

4. Machine Learning Prediction Models

The development of machine learning has enabled computers to function without being supervised. Through machine learning algorithms, various articles have been published analyzing climate quality. These articles use diverse ML models, logical techniques and approaches as the core components to anticipate the speed of the wind. Scientists have established that machine learning algorithms are essential for measuring wind speed. Some of the benefits of using machine learning algorithms are discussed below (Kang et al. 2018).

4.1 Artificial Neural Network Model (ANN)

The structures and networks in the human brain can be simulated by the use of an Artificial Neural Network model. In most cases, the structure of the neural networks is composed of nodes that produce a signal or a signal as per the sigmoid activation function. ANNS are prepared with training inputs and known output information (Warudkar, 2016). In terms of training, edge loads are manipulated to minimize errors that may occur during the process. The modeling analyses a feed forward multi-perception network made up of 12 information hubs, ten concealed layers of hubs 6 and 4, and 1 output nodes, as demonstrated in figure 5 (Kang, 2018).

Label 1 shows that the phase functions at concealed layer nodes are all Gaussian. Training Problem Error Back Campaign, where there are 5-6 working hours until the network performs well against the training set. The second label shows that various architectures have conducted system testing in which few attempts have been successful. In the third label, the structure of the ANN used for theinvestigation, alongside the previous methods, utilized the inductive top-down decision tree, notably, the Oblique Classifier (OCI), which is accounted for improved performance as compared to the standard decision tree algorithms (Ip et al. 2010). The fourth suggests that the general idea of OCI is that at each node, the tree can be split as per algebraic sum of many features, rather than one similar to the standard properties (Yetis et al. 2014).

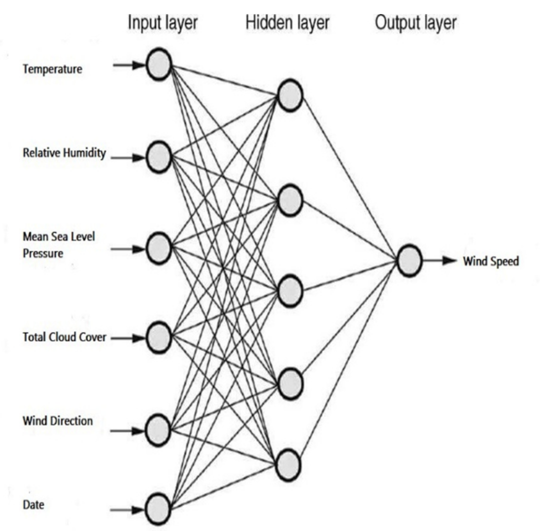

Figure 5. ANN Model for Wind Speed

4.2 Least Squares Support Vector Machine Model

Some scholars consider Square Support Vector Machines, as demonstrated in figure 6 (Yetis and Jamshidi, 2014). Square Support Vector Machine is described as a machine learning technique which is grounded on the theory of statistical learning. It is used in predicting time series and regression, and it has been reported to show good results and overcome many shortcomings associated with MLP. In this paper, scholars say a prediction model grounded on Least Square Support Vector Machines for wind and weather data, which reveal good results (Mbarak et al. 2018).

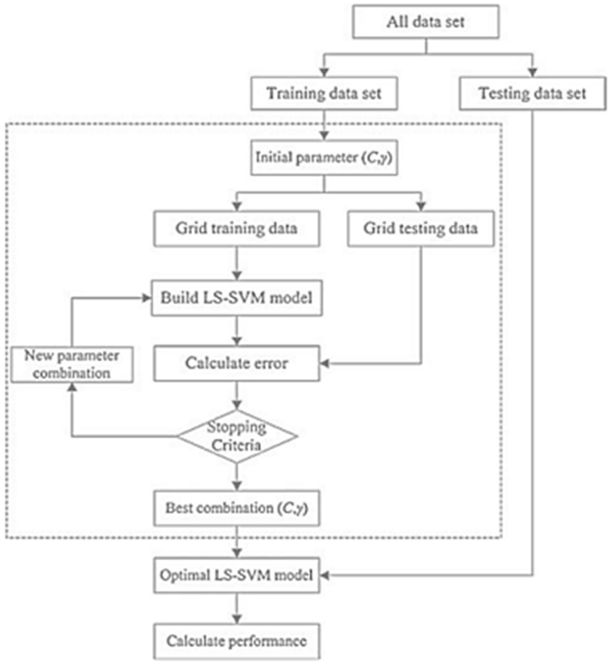

Figure 6. LS-SVW Modelling Structure

5. Wind Modeling and Experimental Results

This section is divided in two parts:

5.1 Wind Rose

The wind Rose is used to show the azimuthal wind speed distribution and direction at a specific area. Wind Rose is essential for showing anemometer data (wind speed and direction) for seated analysis. The most known Wind Rose is made up of 12 equally spatial radial lines (each line representing a compass point) with spatial equal concentric circles, as shown in Figure 7. As shown in the Legend, each wind speed range is denoted with a unique color. In the middle part indicates calm conditions while long lines show the prevailing wind directions. In Figure 8, the Wind Rose shows that at 10 m, the western direction contributes 6.3% of the overall time. The southwest indicated the most reliable and highest wind directions. As shown in Figure 9, the southwest at 900 Mb contributes 11% of the overall time.

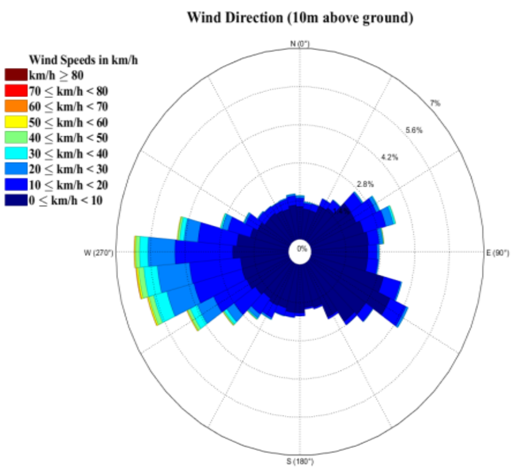

Figure 7. Wind Direction (10m above gnd)

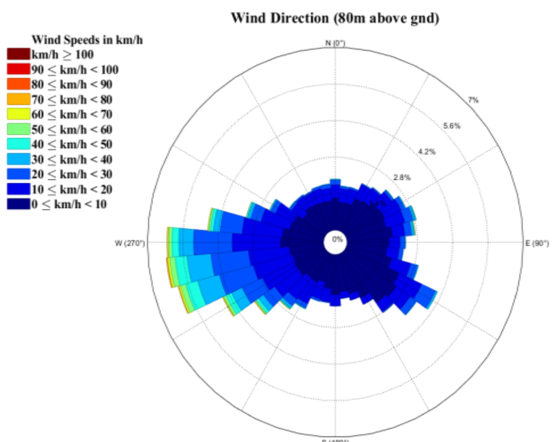

Figure 8. Wind Direction (80m above gnd)

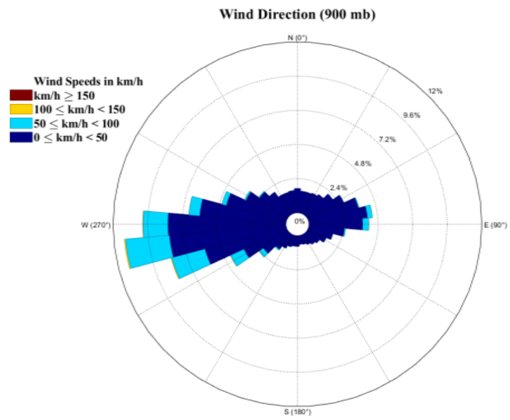

Figure 9. Wind Direction (900mb)

5.2 Wind Speed Forecasting Results

The free parameters (weight and network optimal values) are used in the training process. MLP learning models are characterized by weight connection changes and specific input patterns. In MLP learning models, input layers distribute the input signal to the optimal values of the network, as demonstrated in figure 10. The output layer and the concealed layers comprise a trajectory of processing elements and a stimulation function. The connection weight passes through the signals. A network is considered to be ready for training if it has weight and bias.

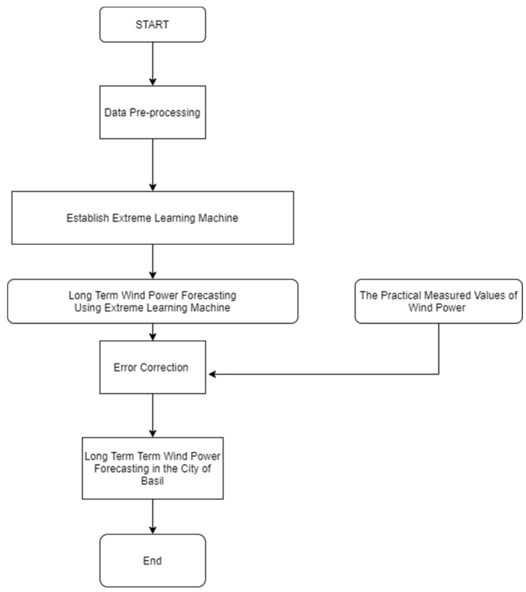

Figure 10. Flow Chart of Wind Power Forecasting Modeling

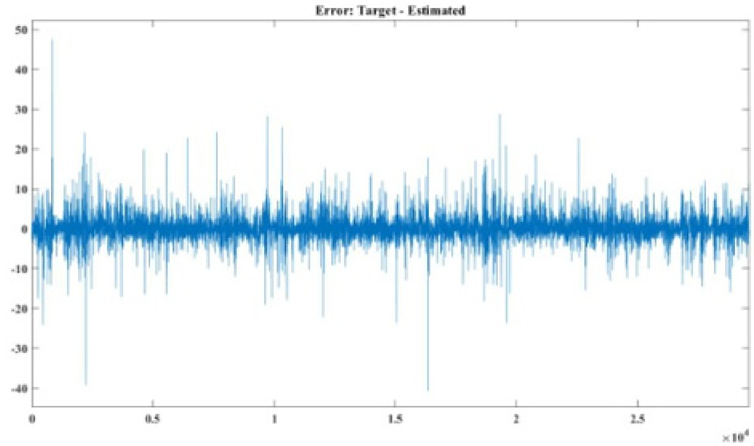

Figure 11-a. Error=Target-Estimated

During training, the adjustment of the network is grounded on output and target comparison. The process of training needs appropriate network behaviour. A set of examples of target outputs are also necessary. Furthermore, the weights and gases in the network are repeated to lessen the functional performance during training. In the feed forward neural network, the Mean Square Error (MSE) was used during the training as the performance function, as shown in figure 11-a and b. Mean Square Error is the average paid error between the target output and the network output (Jamshidi et al. 2016).

In the experiment, data from Switzerland and Bale city was used. Figure 12 shows a comparison of data from Basel city in Switzerland between 1983 and 2018. In Figure 12, input variables of ANN such as humidity, temperature, cloud cover, sea level pressure, sunshine direction, and cloud cover were measured hourly to determine the daytime speed of the wind (Manjili et al. 2013).

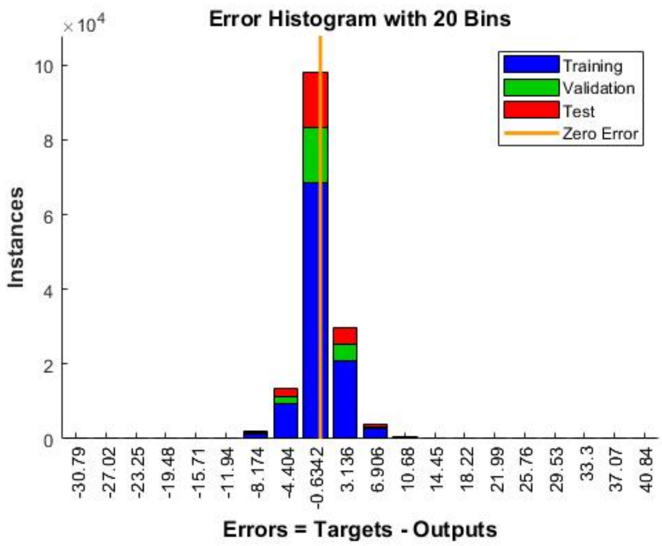

Figure 11-b. Error Histogram

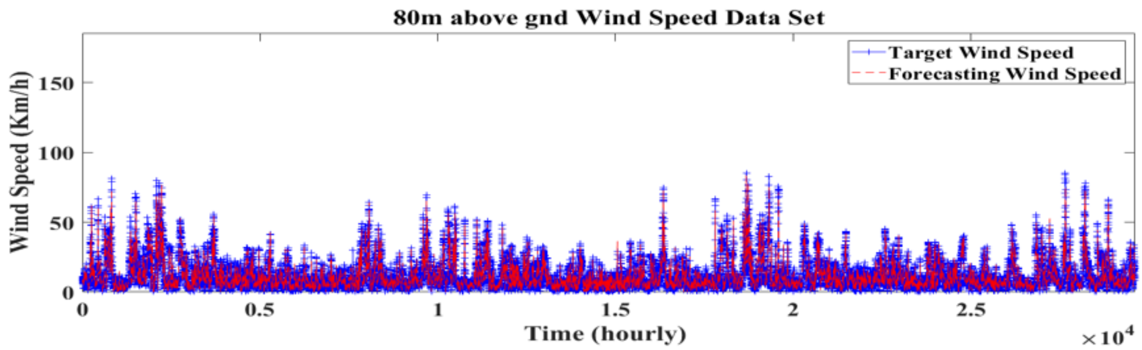

Figure 12. The comparison of actual and predict values for several thousand data between 1983 and 2018 in the city of Basel, a city in northwestern Switzerland

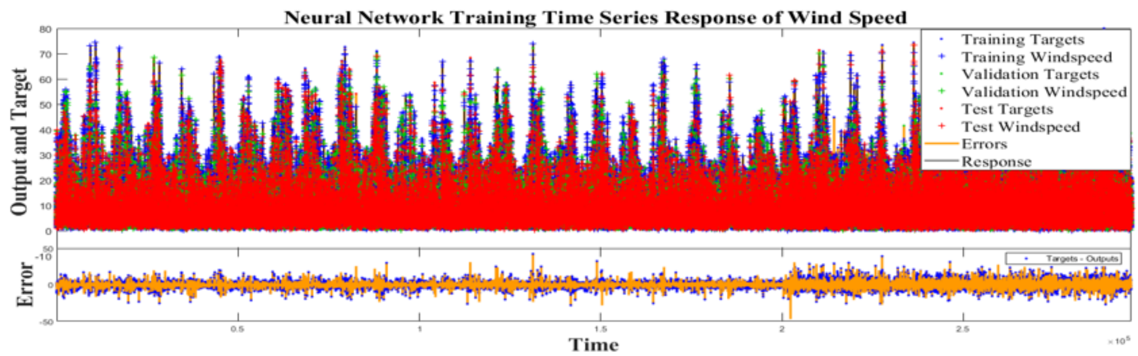

Figure 13. Estimated and real distribution of wind speed (top) and the prediction error (bottom) for the days taking part in testing

For training of neural network training time series response model several data points of average daily wind speed for Basel location are used and for testing data points are utilized. The sensitivity test is performed to validate the number of hidden layer neurons by calculating change in prediction error (MAPE) when number of hidden layer neurons is changed ±5 from hidden layer neurons calculated by equation (Figure 13). Regression is used in the verification of network performance. Two regression plots are used to show the network output during training. They include; validation, and testing the set objectives. A researcher must ensure that data is along the 45 degrees line so as the fit can be perfect. The network outputs are equal to the target at 45 degrees. For this study, there is an ideal fit for all sets of data. In each case, the R-value is 0.975 or higher, as shown in Figure 14.

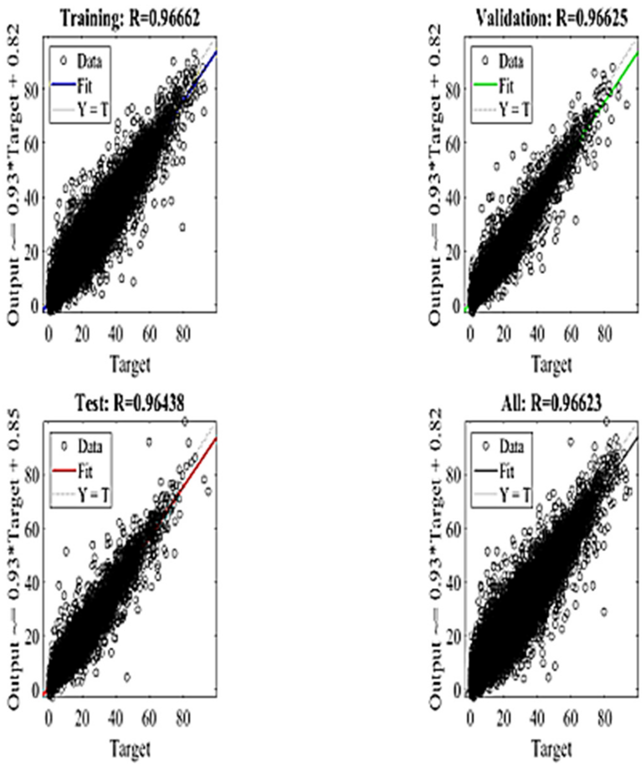

Figure 14. Regression plot for training

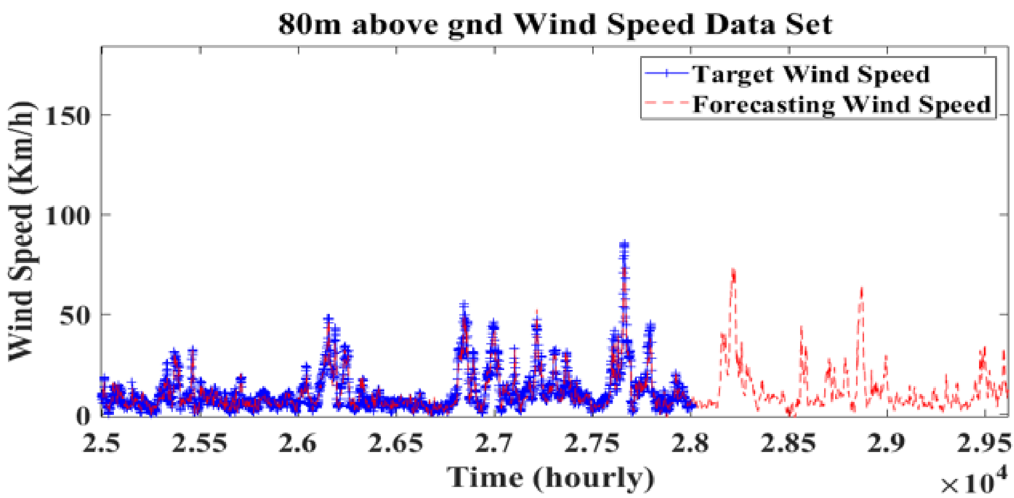

Figure 15. Estimated and real distribution of wind speed (top) and the prediction error (bottom) for the days taking part in testing and forecasting future data

6. Discussion

Data from Basel city is used in the training of neural network training time series response model. In the testing process data, we have used meteorological data and information. All data et simple have been studied and processed in order to be able to find the minimum error between the real data and the estimated data as well as the forecasting of the wind speed as presented in figure 15.

To validate the neurons hidden layer number, the sensitivity test is carried out through calculating prediction error change (MAPE) when neurons hidden layer number is changed ±5 from concealed layer neurons calculated by equation.

To predict the speed of wind in an area, the Multilayer Perception (MLP) neural network architecture is used. The MLP must have a MAPE of at least 6.32%. The ANN model performance plot shows that an increase in the number of epochs minimizes the mean square error (Yetis et al. 2016).

An epoch is one complete sweep of validation, training, and testing. The validation set error and the test set error has similar characteristics; therefore, they do not overfit each other near the epoch. The R-value shows the relationship that exists among the target value and the outputs of an ANN model (Tannahill et al. 2013).

When data falls along the 45-degree line, scholars call it a perfect fit (slope is close to 1), and this means that the network output is equal to targets and the correlation coefficient is 0.966. The NF tool developed the ANN model, which predicts the speed of wind close to the values measured. The ANN model is used to measure the speed of wind in Basel, and the data is shown in figure 15. From the measurement, the MAPE is 6.329%, and this shows the ANN high accuracy. From the same location, the R-value is about 0.97, and during the validation process, the slope is 0.966, and this, therefore, makes the ANN model fit to measure the wind speed in Switzerland.

Meteorological Data from the database between 1983 and 2018 is used as input for ANN Model. The variables used include wind speeds of the previous days and years, maximum temperature, average temperature, air pressure, minimum temperature, altitude and solar radiation. Table 2 shown the speed of wind variation in different years.

This proposed approach will be very useful for multi-source systems in smart grids or microgrids at the service of a smart city (Kazerani et al. 2020) (Kaplan et al.2021) for future research works.

7. Conclusion

This paper has presented a system that can be used in predicting the speed of wind daily in the next few years in the Basel area. The average MAPE and R-value obtained from the daily wind speed prediction are found to be 6.35% and 96.6 respectively.

The presented results of the experiments were obtained over several runs using data arranged in a random manner. This was done to assess the predictive properties of the system in the most objective way. Two important elements play an essential role in the production of energy in a wind farm, the first is the detection of the wind speed and its direction and the second is the design of the blade profile of the wind turbines. These results show the accuracy of this method using artificial neural network based on ML. We have used more information and data in this research. We used data of the city of Basel in Switzland between 1983 and 2018. In the forecasting method when we have more information, in this case, the accuracy of the results is guaranteed. In future research, we will apply this forecasting method for a multi power source (PV and wind turbine).

Conflicts of Interest

Declare conflicts of interest or state “The authors declare no conflict of interest” for this paper.

References

Arslan, Talha, Y. Murat Bulut, & Arzu Altın Yavuz. (2014). Comparative study of numerical methods for determining Weibull parameters for wind energy potential. *Renewable and Sustainable Energy Reviews, 40*, 820-825. https://doi.org/10.1016/j.rser.2014.08.009

Bremnes JB. (2002). Probabilistic wind power forecasts by means of statistical model. Proceedings of IEA R&D Wind Annex XI Joint Action Symposium on Wind Forecasting Techniques, Norrköping, 103–114. 2.

Chang, Tian Pau. (2011). Performance comparison of six numerical methods in estimating Weibull parameters for wind energy application. *Applied Energy, 88*(1), 272-282. https://doi.org/10.1016/j.apenergy.2010.06.018

Chen X., Agarwal R. (2013). Optimization of FX, DU and NACA airfoils for wind turbine blades using a multi-objective genetic algorithm. Proceedings of the 51st AIAA Aerospace Sciences Meeting, Grapevine, TX, 7-10 January 2013, AIAA Paper 2013-07. https://doi.org/10.2514/6.2013-782

D.Liu, D.Niu, H.Wang, L.Fan. (2014). Short-term wind speed forecasting using wavelet trans-form and support vector machines optimized by genetic algorithm. *Renewable Energy, 62*, 5927. https://doi.org/10.1016/j.renene.2013.08.011

George, Florence. (2014). A comparison of shape and scale estimators of the two-parameter Weibull distribution. *Journal of Modern Applied Statistical Methods, 13*(1). https://doi.org/10.22237/jmasm/1398916920

IG. Damousis ,P. Dokopoulos. (2001). A fuzzy expert system for the forecasting of wind speedand power generation in wind farms. In: Proceedings of power industry computer appli-cations, 2001. PICA 2001. Innovative computing for power-electric energy meets themarket. 22nd IEEE Power Engineering Society international conference on. Sydney:IEEE; 2001. p. 6369.

Ip, W. F., Vong, C. M., Yang, J. Y., & Wong, P. K. (2010, August). Least squares support vector prediction for daily atmospheric pollutant level. In 9th IEEE/ACIS International Conference on Computer and Information Science (pp. 23-28). IEEE. https://doi.org/10.1109/ICIS.2010.34

J. Hu & A. -V. Vasilakos. (2016). Energy Big Data Analytics and Security: Challenges and Opportunities. *IEEE Transactions on Smart Grid, 7*(5), 2423-2436. https://doi.org/10.1109/TSG.2016.2563461

Jamshidi, M., Tannahill, B., Ezell, M., Yetis, Y., & Kaplan, H. (2016). Applications of big data analytics tools for data management. In Big data optimization: Recent developments and challenges (pp. 177-199). Springer, Cham. https://doi.org/10.1007/978-3-319-30265-2_8

Jamshidi, M., Tannahill, B., Yetis, Y., & Kaplan, H. (2015). Big data analytic via soft computing paradigms. In Frontiers of higher order fuzzy sets (pp. 229-258). Springer, New York, NY. https://doi.org/10.1007/978-1-4614-3442-9_12

Jursa R & Rohrig K. (2008). Short-term wind power forecasting using evolutionary algorithms for the automated specification of artificial intelligence models. *International Journal of Forecasting, 24*(4), 694–709. https://doi.org/10.1016/j.ijforecast.2008.08.007

Kang, G. K., Gao, J. Z., Chiao, S., Lu, S., & Xie, G. (2018). Air quality prediction: Big data and machine learning approaches. *International Journal of Environmental Science and Development, 9*(1), 8-16. https://doi.org/10.18178/ijesd.2018.9.1.1066

Kaplan, H. Tehrani, K, & Jamshidi, M. (2021). Fault Diagnosis of Smart Grids Based on Deep Learning Approach. 2021 World Automation Congress (WAC), 2021, 164-169. https://doi.org/10.23919/WAC50355.2021.9559474

Kazerani.M, Tehrani.K. (2020). Grid of Hybrid AC/DC Microgrids: A New Paradigm for Smart City of Tomorrow, 2020 IEEE 15th International Conference of System of Systems Engineering (SoSE), 2-4 June 2020, p.1-6, Budapest, Hungary. https://doi.org/10.1109/SoSE50414.2020.9130482

Lau A. (2011). Probabilistic wind power forecasts: From aggregated approach to spatio-temporal models. Ph.D. dissertation, Mathematical Institute, University of Oxford.

Lee, D. (2017). Very short-Term wind power ensemble forecasting without numerical weather prediction through the predictor design. *J. Electr. Eng. Technol., 12*, 2177–2186. 6.

Li G., Shi J. (2010). On comparing three artificial neural networks for wind speed forecasting. *Applied Energy, 87*, 2313–20. https://doi.org/10.1016/j.apenergy.2009.12.013

Manjili, Y. S., Vega, R., & Jamshidi, M. (2013). Cost-efficient environmentally-friendly control of micro-grids using intelligent decision-making for storage energy management. *Intelligent Automation & Soft Computing, 19*(4), 649-670. https://doi.org/10.1080/10798587.2013.842346

Mbarak, A., Yetis, Y., & Jamshidi, M. (2018, June). Data-Based Pollution Forecasting via Machine Learning: Case of Northwest Texas. In 2018 World Automation Congress (WAC) (pp. 1-6). IEEE. https://doi.org/10.23919/WAC.2018.8430438

Nielsen HA, Madsen H & Nielsen TS. (2006). Using Quantile Regression to Extend an Existing Wind Power Forecasting System with Probabilistic Forecasts. *Wind Energ., 9*, 95–108, 95-108. Published online 19 December 2005 in Wiley Interscience. https://doi.org/10.1002/we.180

Noorollahi, Y.; Jokar, M.; Kalhor. (2016). A. Using artificial neural networks for temporal and spatial wind speed forecasting in Iran. *Energy Convers. Manag., 115*, 17–25. https://doi.org/10.1016/j.enconman.2016.02.041

Ribeiro A.F.P, Awruch A.M Gomes H.M. (2012). An airfoil optimization technique for wind turbines. *Applied Mathematical Modelling Journal, 36*(10), 4898-4907. https://doi.org/10.1016/j.apm.2011.12.026

Ronit K. Singh, M. Rafiuddin Ahmed, Mohammad Asid Zullah, Young-Ho Lee. (2012). Design of a low Reynolds number airfoil for small horizontal axis wind turbines. *Renewable Energy, 42*, 66-76. https://doi.org/10.1016/j.renene.2011.09.014

Sarkar, A., & Pandey, P. (2015). River water quality modelling using artificial neural network technique. *Aquatic Procedia, 4*, 1070-1077. https://doi.org/10.1016/j.aqpro.2015.02.135

T. Arslan, Y.M. Bulut, A.A. Yavuz. (2014). Comparative study of numerical methods for determining Weibull parameters for wind energy potential. *Renewable and Sustainable Energy Reviews, 40*, 820-825.

Tannahill, B. K., Maute, C. E., Yetis, Y., Ezell, M. N., Jaimes, A., Rosas, R., & Jamshidi, M. (2013, June). Modeling of system of systems via data analytics—Case for “Big Data” in SoS. In 2013 8th International Conference on System of Systems Engineering (pp. 177-183), IEEE.

Tastu J, Pinson P, Trombe PJ, & Madsen H. (2014). Probabilistic forecasts of wind power generation accounting for geographically dispersed information. *IEEE TRANSACTIONS ON SMART GRID, 5*, 480-489. https://doi.org/10.1109/TSG.2013.2277585

Warudkar, Vilas, S. Ahmed, & Prem Kumar Chaurasiya. (2016). Application of remote sensing in wind resource assessment: a comparative analysis. In Proceedings of the 15th World Wind Energy Conference, Tokyo, Japan, vol. 31. 2016.

Yahyaoui I, Cantero A. S. (2018). Modeling and Characterization of a Wind Turbine Emulator, in Advances in Renewable Energies and Power Technologies Journal, Elsevier. https://doi.org/10.1016/B978-0-12-812959-3.00016-2

Yetis, Y., & Jamshidi, M. (2014, August). Forecasting of Turkey's electricity consumption using Artificial Neural Network. In World Automation Congress (WAC), 2014 (723-728). IEEE. https://doi.org/10.1109/WAC.2014.6936121

Yetis, Y., Kaplan, H., & Jamshidi, M. (2014, August). Stock market prediction by using artificial neural network. In World Automation Congress (WAC), 2014 (pp. 718-722). IEEE. https://doi.org/10.1109/WAC.2014.6936118

Zhang, C.; Zhou, J.; Li, C.; Fu, W.; Peng, T. (2017). A compound structure of ELM based on feature selection and parameter optimization using hybrid backtracking search algorithm for wind speed forecasting. *Energy Convers. Manag., 143*, 360–376. https://doi.org/10.1016/j.enconman.2017.04.007

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