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Medium-Term Wind Speed Prediction using Bayesian Neural Network (BNN)

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Abstract

Renewable energy has become an emerging source of daily energy utilization in recent years. Non-conventional sources are extensively applied in the smart grid due to their environment friendly and relatively easy maintenance. Wind energy unlike other conventional sources has drawn attention in terms of clean energy production. Due to unpredictable nature of wind, it is difficult to trade energy to the smart grid without any power loss. Variations in wind energy affect power scheduling, wind power generation, and energy management. Therefore, wind speed forecasting is an important tool to address such problems. Machine learning approaches have always been considered for accurate wind speed prediction. To evaluate the performance of machine learning algorithms, several models have been tested to achieve precise prediction. Amongst these several models, Neural Networks perform best and optimizes the prediction at its maximum. Apropos, in this paper, Bayesian Neural Network (BNN) is used for predicting medium-term wind speed on different time horizons. The input for training purposes is taken from Numerical Weather Prediction (NWP) model and sifted as per the model's requirement. After successive training, it is evident from the percentage Mean Absolute Percentage Error (MAPE) and Normalized Mean Absolute Error (NMAE) criterion that BNN has achieved good accuracy as compared to Least Absolute Shrinkage and Selection Operator (LASSO). Ultimately, the proposed model has shown that it can bring precision and accuracy for prediction and can be applied for other renewable sources as solar and water as well.

Keywords: Bayesian Neural Network (BNN), Least Absolute Shrinkage and Selection Operator (LASSO). Medium-term wind speed prediction, Numerical Weather Prediction (NWP).

1. Introduction

Among all other renewable energy sources, the share of wind energy is increasing day by day globally. Wind energy supplies 4.7% of electric power Worldwide (Dyatlov, Didenko, Ivanova, Soshneva, & Kulik, 2020). The rise in wind energy usage has drawn attention towards forecasting because large-scale integration of wind energy needs accuracy and precision in forecasting. Accurate and effective power generation forecast systems are needed to combat wind energy sources intermittency and variable nature. Days-ahead forecasting is planned and organized from the perspective of the wind power plant owner. The demand for days-ahead forecasting is highly used, especially for the power grid's energy trade, transmission, distribution, optimization, and security (Nema, Nema, & Rangnekar, 2009; Ogundiran, 2018).

Numerous amounts of work have been established in the domain of wind speed forecasting. Primarily, it has been observed that forecasting is done on the bases of time horizon. The time scale for forecasting purpose, influences, decision-making, as the ranges are discussed briefly (Prakesh, Sherine, & BIST, 2017).

Short-term (from few seconds to hours): It is purposely used for storage control and the electricity market. In the smart grid, short-term forecasting plays an important role.

Medium-term (from 6 to 72 hours ahead): this range is a bit crucial to handle deciding management and planning. It deals with economic dispatch and operational management of the grid.

Long-term (up to one week ahead): It is helpful for maintenance, scheduling, and distribution of utilities, etc.

Moreover, the forecasting also includes the nature and structure of wind power plant, terrain and data (Buhan & Çadırcı, 2015) (Buhan, Özkazanç, & Çadırcı, 2016). Wind speed generation forecasting is categorized into three models, which are physical, statistical, and hybrid models. As the names suggest, physical models which process the physical data are usually obtained from NWP or wind power plant' s landscape. The statistical model depends upon the historical meteorological data, while the hybrid model is the combination of physical and statistical models that have captivated more researchers (Zhou, Wang, & Zhang, 2019).

Depending on the time horizon, a suitable forecasting model is selected (Soman, Zareipour, Malik, & Mandal, 2010). There are typically two kinds of statistical forecasting models that are linear and non-linear. In the previous research carried out in this field, it has been seen that both models are widely adopted for prediction purposes. Linear models generally deal with statistical and historical data. It can be safely compared with the persistence model (Soman et al., 2010). Typically, linear models that have been used extensively are Linear Regression (LR), Autoregressive with exogenous variable (AR), Autoregressive with integrated moving average (ARIMA), and Kalman filtering. While on the other hand, non-linear models are generally operated with NWP models, which predict weather parameters and range from Artificial Neural Networks (ANN), Support Vector Machine (SVM), and Fuzzy logics are the best machine learning algorithms (Y. Liu, Zhang, Chen, & Wang, 2018) (Lydia, Kumar, Selvakumar, & Kumar, 2016).

2. Literature Review

Forecasting is an essential feature in the operations of the grid. It regularizes and manages the performance of an energy management system (EMS). The main challenge behind forecasting the wind speed or is its volatile and variable nature. The unpredictable and intermittent nature of wind speed creates hurdles in the planning and controlling of a grid system (H. Liu, Duan, Wu, Li, & Dong, 2019). Therefore, the system requires an efficient and accurate predictive tool to solve this issue at its best. (Ahadi & Liang, 2018) proposed a neural network model to predict wind speed time series. The proposed neural network is trained with different training models, such as Bayesian Regularization, Levenberg-Marquardt, and Scaled-conjugate gradient. The results were compared with ARMA and showed that the neural network approach demonstrates more accurate output. It is observed very keenly that wind speed forecasting serves to schedule and dynamic control of power management systems. (Ye, Ding, & Wan, 2021) distinguishes few facts about wind speed's randomness, irregularity, and non-linear nature and brought significance in using the Bayesian model. The study added more than the Bayesian model with Gaussian process prior is adopted for high flexibility, probabilistic evaluation, and predictive variance. It was concluded from the research that Bayesian modeling is a good choice as a predictive tool for predicting wind speed.

On the other hand, deep learning seems to be in the limelight in recent studies. Especially when forecasting is involved, deep learning using Long term short memory

(LSTM) has got researcher's attention. (Bali, Kumar, & Gangwar, 2019) stated that the implementation of extensive data set for prediction purposes is a big challenge to be catered to. But, the usage of LSTM can solve this problem by having a deep analysis of the data set. LSTM is known for its accuracy and pattern remembrance for a more extended period. The LSTM model concludes that wind speed can be best predicted with deep learning models and can bring efficiency to the system. Furthermore, lots of disputes have been seen when dealing with the data set. Pre-processing and sifting of the data set have been taken as an arduous task for further training.

The thumb rule of using any machine learning model is to make the data set able to train. (H. Liu, Mi, & Li, 2018) used different predictive tools for different purposes. This study reveals that the decomposition and organization of the data itself is an important thing to consider. Empirical wavelet transform is used to mortify the data set then LSTM is employed to the data arrays with low frequency. At the same time, Elman Neural Network is used for higher frequency data arrays. It is worth noticing that using a combination of machine learning models for a different purpose can achieve high accuracy in predicting wind speed.

The literature review shows that non-linear machine learning approaches are more effective in terms of accurate prediction. In (Y. Wang, Shen, Mao, Chen, & Zou, 2018) Wang has combined least absolute shrinkage and selection operator (LASSO) with long short-term memory (LSTM) for short term prediction of solar intensity where combined model better effectiveness and accuracy. Similarly, LASSO has been used for solar power generation forecasting in (Tang, Mao, Wang, & Nelms, 2018), whereas no evidence has been found where LASSO has been used for medium term wind speed prediction. In (Blanchard & Samanta, 2020), different ANN models are used to predict wind speed. The results show that non-linear autoregressive (NAR) and non-linear autoregressive with exogenous input (NARX) have achieved better accuracy than the persistence model. Another research conducted in 2019 revealed that any neural network and its respective kind could enhance wind speed forecasting. Besides, feed-forward neural networks are primarily used in prediction, forecasting, or classification (J. Wang, Zhang, & Lu, 2019). In (Ashraf, Raza, & Saleem, 2020) and (Kaur, Kumar, & Segal, 2016), the performance and optimization of different networks are shown. It has been perceived that neural networks with different parameters can attain high accuracy and precision compared to linear models.

In this research work, medium-term wind speed forecasting is originated by employing a feed-forward neural network with a Bayesian regularization training model and LASSO for making a comparison in terms of checking accuracy. Bayesian regularization training model will be called as Bayesian Neural Network (BNN). The study's fundamental approach is to predict 6 to 72 hours ahead wind speed of the wind power plant situated in Sindh, Pakistan. This research's main objective is to observe the performance of Bayesian regularization with the mentioned time horizon scale. In short-term wind speed forecasting, the persistence model is usually used to compare the precision, but in the medium term, the forecasting persistence model is not useful (Ahmed & Khalid, 2018). In a study by (Kumar & Sahay, 2018) different neural networks with different training models are adopted and are used for wind speed forecasting. This research primarily shows that when BNN is compared with a linear model LASSO, where it attains good accuracy for predicting wind speed. In addition, BNN ignores uncertainties at its best and updates the weights to extend the standard network with maximum likelihood. In this study, mainly BNN is employed for medium term wind-speed forecasting and for comparative analysis LASSO has been used for observing the efficacy.

Bayesian Neural Network (BNN)

Bayesian Neural Networks contain a unique function of regularization with probabilistic approach. This is one of the classic training models used in regression and classification. It is also noted that BNN's are very much flexible in designing the architecture of the network. Deciding the inputs, hidden layers, and adjustment of distributive weights are easy and effortless in BNN (Niu, Fang, & Niu, 2019). Fig. 1 indicates every connection of input relates to neurons of a hidden layer with a distribution of adjacent weights.

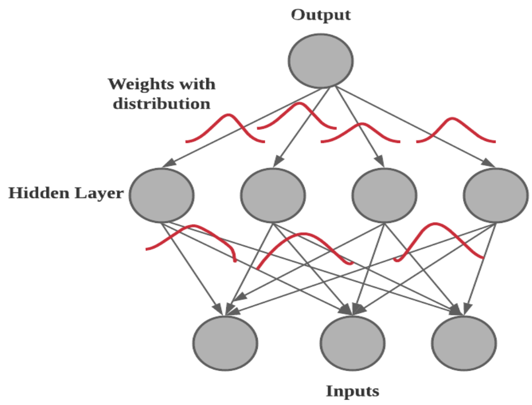

Fig. 1. The Architecture of BNN

The distributed weights are approaching the Probability Density Function (PDF). Using the Bayes theorem, these pdf generated weights are called prior to distributions, which are later converted into the posterior distribution (Maiti, Kumar, Sarkar, Tiwari, & Srinu, 2019). The mathematical expression of the Bayes theorem is shown below in Eq. (1), with X and Y are the events and the rest of them are the probabilities of events chosen.

$$P(Y \mid X) = \frac{P(X \mid Y) \bullet P(Y)}{P(X)} \tag{1}$$

This probability is often called evidence of the model. In neural networks, training occurs with a different number of neurons and is assembled with their respective evidence. Eq. (2) and Eq. (3) show the architecture of neural networks concerning their evidence or PDF, whereby y is the desired output, x is the input, w is the distributed weight, and φ is an activation function.

$$y = w_1(P(y \mid x))x_1 + w_2(P(y \mid x))x_2 + w_3(P(y \mid x))x_3 + ... + w_n(P(y \mid x))x_n \tag{2}$$

$$v = \phi(y) \tag{3}$$

$$\phi = \frac{1}{1 - \exp(-az))} \tag{4}$$

As illustrated in the equations and the architecture, Bayes theorem has attached a probability to the training model and estimated the forecast. Furthermore, it has also been seen that it can be used as a selection parameter.

3. Model Implementation

The data obtained from the NWP model is pre-processed and assembled according to the proposed predictive model. The data comprises of wind speed in 3-hour resolution up to 72 hours. BNN has always been considered ideal for short term wind speed prediction ranging from 0-6 hours. Here, this has been extended for medium term prediction with a continuous range of 6-72 hours (~3 days ahead). Each hour is trained individually for checking the efficacy and accuracy. BNN model is always used for optimization in prediction models whereas here it has been implemented in two phases, which are training and testing of NN. Seventy percent of the data is allotted for training, while the rest is for testing and validation. The training phase apparently depends on the architecture of the neural network. The parameters chosen for training are indicated below in Table 1. It clearly shows that only wind speed (m/s) is chosen as a variable and has the desired output of the same dimension at the input. After a hit and trial of choosing hidden layers, 30 hidden layers are decided for further continuation.

Table 1. Selected parameters for training the model.

Parameters	Values
Input layer	343×1
Hidden layer	30
Output layer	343×1
Train indices	292×1
Test indices	51×1
Validation indices	51×1
Epochs	982
Best epoch	79
Gradient	847
Mu	0.0050

The simulated architecture of BNN is shown in Fig. 2, with w is the weight and b is biases contained in the neural network.

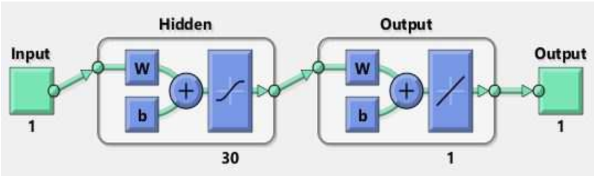

Fig. 2. The simulated architecture of BNN.

Proposed Methodology

As mentioned above, BNN is chosen as a predictive model for forecasting medium-term wind speed along with LASSO as a comparative model. Wind speed is irregular and is not steady always, due to which pre-processing of data is a bit crucial for training and testing purpose. The flowchart of the proposed methodology is demonstrated in Fig. 3. The trend by the NWP data has been depicted in Fig. 4, which can serve as a pattern for showing the raw data for making comparisons with outputs. A step by step demonstration of the procedure from Fig. 3 is given below as:

The physical data is obtained from the NWP model. The chosen variable is wind speed (m/s). The data set is organized in 3-hour resolution from 6 to 72 hours ahead of the 2016 year. The data is sifted according to the predictive model as shown in Table 1.

In every supervised machine learning algorithm, selecting a target or response is a crucial step to follow. The target acts as a catalyst between input and the desired output. Thus, the target is chosen according to the output needed. In this paper, the observed wind speed is taken as the target.

After the successive pre-processing of data, the data set is ready to employ to BNN. Seventy percent of the data samples are utilized for the training and the rest for the testing and validation. The tested sample's accuracy is checked through statistical measures: Mean Absolute Percentage Error (MAPE) and Normalized Mean Absolute Error (NMAE). These quantifying measures are shown in Eq. (5) and Eq. (6), where z is the actual wind speed, while z' is the final predicted wind speed.

$$MAPE = \frac{1}{N}\sum_{i=0}^{n}\left|\frac{z-z'}{z}\right| \times 100 \quad (5)$$

$$NMAE = \frac{\sum_{i=0}^{n}\left|z-z'\right|}{N} \quad (6)$$

If the MAPE and NMAE criterion is satisfied in the wake of accuracy, then the prediction is successful. The estimation of the MAPE and NMAE depends upon some threshold values which define accuracy level. If the MAPE is achieved below 10 percent, it is considered a higher accuracy or good accuracy. While in the context of NMAE, if the NMAE is achieved less than 1 %, the accuracy goals are achieved (Nespoli et al., 2019) (L. Wang, Lv, & Zeng, 2018).

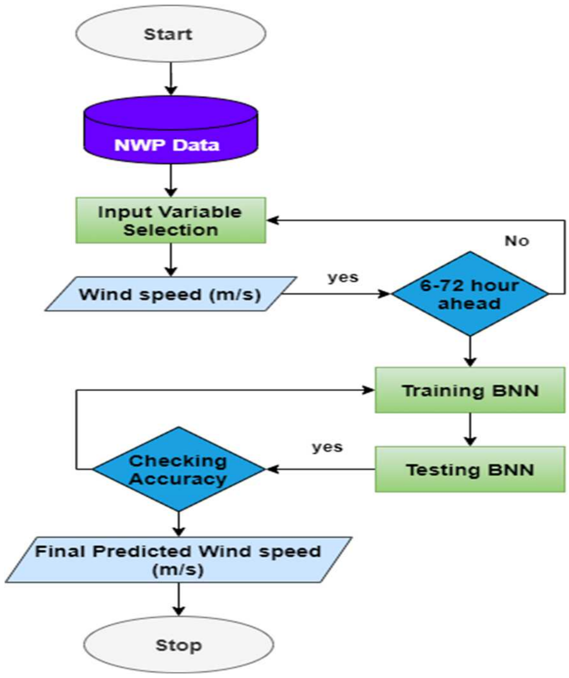

Fig. 3. Flowchart of the proposed methodology.

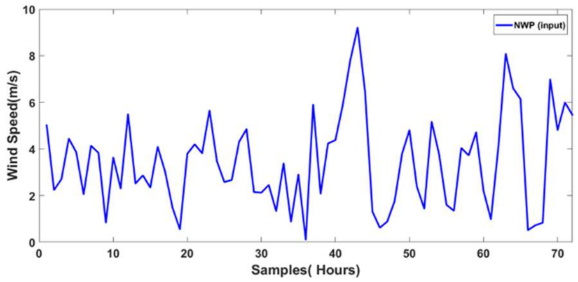

Fig. 4. Trend by NWP data (Original data).

Simulations and discussions

The final predicted wind speed is measured for every 3-hour resolution from 6 to 72 hours ahead for both BNN and LASSO. As the nature of wind speed is always discontinuous, it is hard to decide when the NWP model is forecasting the wind speed. Therefore, for addressing this problem, prediction is made possible to remove the errors between actual and predicted wind speed.

As shown in Table 2, the MAPE and NMAE are used as performance evaluators showing some magnificent accuracy. The BNN model has attained and fulfilled the NMAE criterion of having less than 1% estimation, which is evident from the results. While on the other hand, the estimation from MAPE is dwindling between good to reasonable accuracy. Few of the hours are showing reasonable accuracy above 20 percent. Whereas LASSO has been selected as a comparative model and its quantifying measures are listed in Table 3, where it is evident that the MAPE values are very poor as compare to BNN. Conclusively, it has been observed that BNN has achieved good accuracy in terms of quantifying measures. The forecasting estimation performance for MAPE and NMAE for BNN is shown in Fig. 5 and Fig. 6, respectively.

Table 2. Quantifying measures for BNN.

Hours	MAPE	NMAE	Hours	MAPE	NMAE
9 Hour ahead	19.01	0.003	42 Hour ahead	11.90	0.03
12 Hour ahead	19.39	0.001	45 Hour ahead	17.37	0.04
15 Hour ahead	16.4	-0.021	48 Hour ahead	25.29	0.06
18 Hour ahead	12.71	0.029	51 Hour ahead	30.86	0.083
21 Hour ahead	15.98	0.04	54 Hour ahead	20.79	0.03
24 Hour ahead	33.33	0.03	57 Hour ahead	24.13	0.068
27 Hour ahead	16.81	-0.002	60 Hour ahead	22.58	0.05
30 Hour ahead	18.87	0.01	63 Hour ahead	20.32	-0.02
33 Hour ahead	18.20	-0.03	66 Hour ahead	15.31	0.02
36 Hour ahead	20.84	-0.02	69 Hour ahead	18.16	0.04
39 Hour ahead	18.79	0.002	72 Hour ahead	26.9	0.08

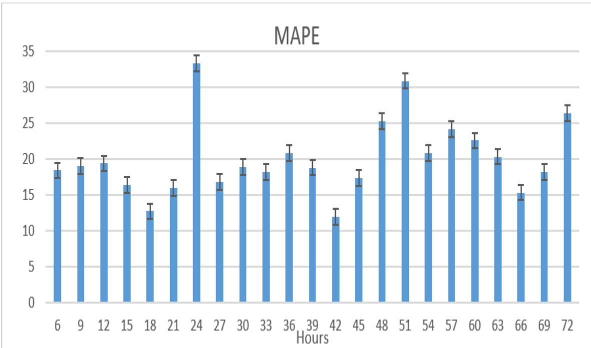

Fig. 5. MAPE criterion for BNN (6 to 72 hours ahead).

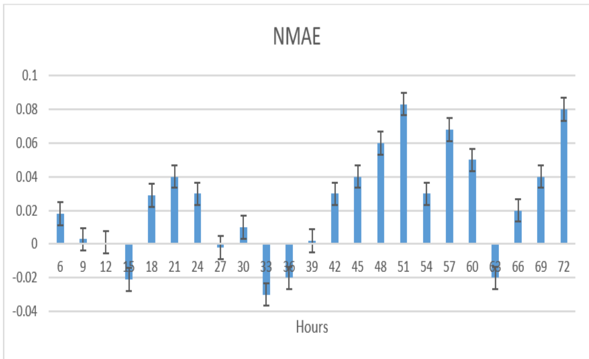

Fig. 6. MAPE criterion for BNN (6 to 72 hours ahead).

Table 3. Quantifying measures for LASSO

Hours	MAPE	Hours	MAPE
9 Hour ahead	249.3	42 Hour ahead	35.84
12 Hour ahead	41.13	45 Hour ahead	36.49
15 Hour ahead	39.99	48 Hour ahead	41.84
18 Hour ahead	36.9	51 Hour ahead	50.89
21 Hour ahead	36.32	54 Hour ahead	42.3
24 Hour ahead	56.8	57 Hour ahead	39668.1
27 Hour ahead	-16670	60 Hour ahead	40.75
30 Hour ahead	40.32	63 Hour ahead	37.45
33 Hour ahead	39.01	66 Hour ahead	35.26
36 Hour ahead	43.41	69 Hour ahead	36.27
39 Hour ahead	38.09	72 Hour ahead	42.6

For checking the precision in machine learning algorithms, the trend between output and the chosen target should be absolute. Wind speed characteristics of several hours such as 9, 36, 48, 57, and 72 are shown in Fig. 7, Fig. 8, Fig. 9, Fig. 10, and Fig. 11, for observing the trend between target and output. The above mentioned predicted hours showed unique trends, but the other predicted hours were following the same trend which are only exhibited in Table 2. Fig. 7(i) and 7(ii) shows 9 hours ahead prediction for LASSO and BNN respectively. For LASSO, it can be seen that there are no intersecting peaks to observe. The troughs and crests of trends are not showing regularity between output and target which means the there is no accuracy in prediction by LASSO. However, it can be observed that there is a minimal difference between target and output for BNN, which highlights good accuracy by the proposed predictive tool.

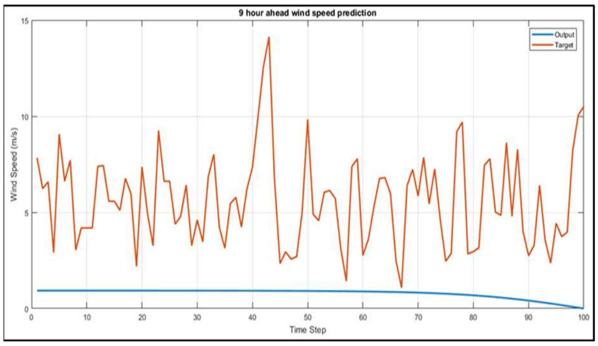

Fig. 7(i). 9 Hour ahead wind speed prediction (LASSO).

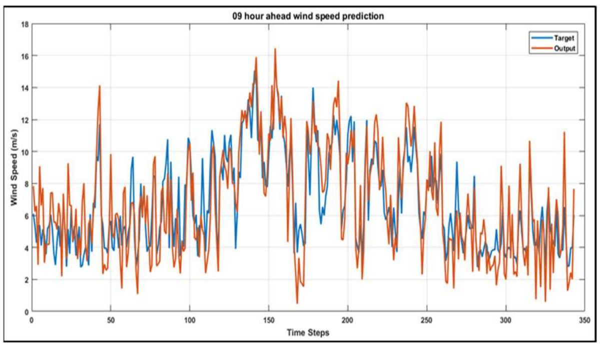

Fig. 7(ii). 9 Hour ahead wind speed prediction (BNN)

After completion of two days, the trend is getting closer and showing precision and efficiency for BNN. These trends have been presented in Fig. 8, Fig. 9, Fig. 10, Fig. 11(i), and Fig. 11(ii) for 36, 48, 57, and 72 hours ahead, respectively. In all the cases, LASSO did not perform well where it was found having no intersecting point between target and output nor was there any convergence observed in Fig. 11(i). Whereas a clear pattern of convergence can be observed in these figures between target and output, which indicates that the BNN model has outperformed well and removed the possible outliers between the target and output.

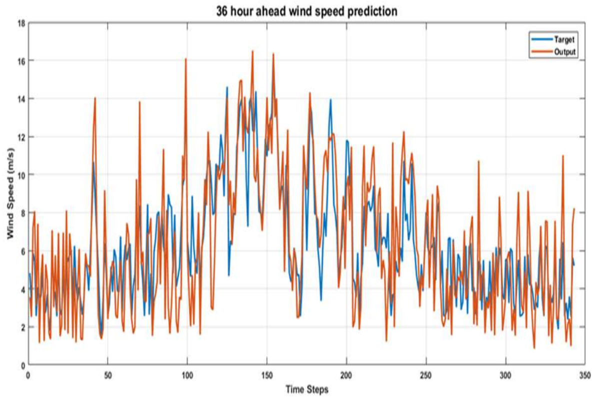

Fig. 8. 36 Hour ahead wind speed prediction (BNN).

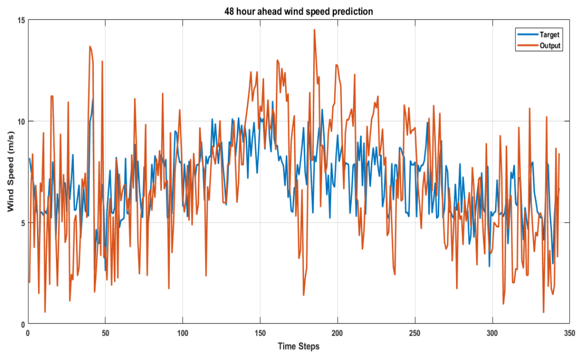

Fig. 9. 48 Hour ahead wind speed prediction (BNN).

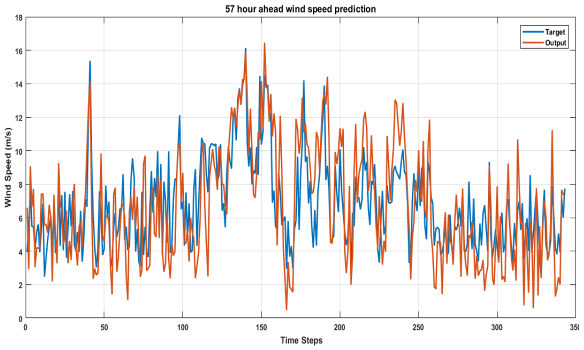

Fig. 10. 57 Hour ahead wind speed prediction (BNN).

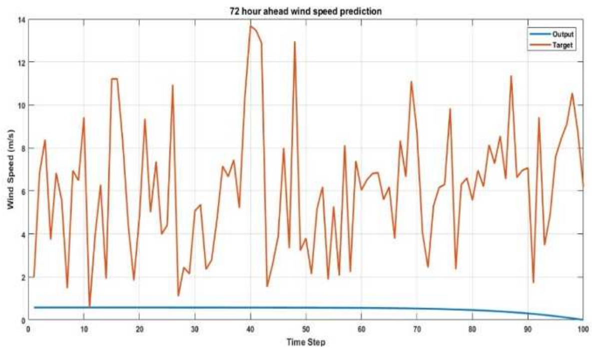

Fig. 11(i). 72 Hour ahead wind speed characteristics (LASSO).

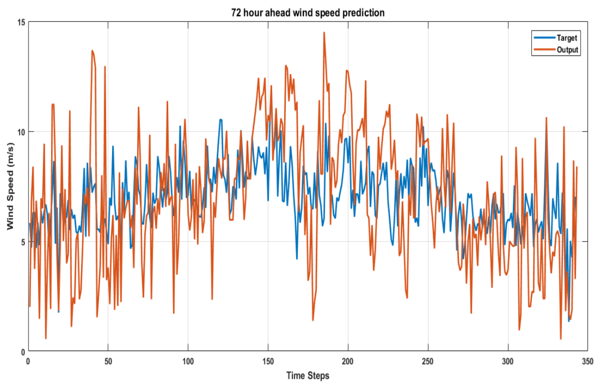

Fig. 11(ii). 72 Hour ahead wind speed characteristics (BNN).

These results mentioned above indicate that, LASSO is not an ideal approach for wind and other power predictions. While on the other hand BNN is an ideal candidate for medium-term wind speed forecasting. As the prediction duration increases, the values are still accurate, and no extreme irregularity has been observed.

4. Conclusions

The surge in need for wind speed forecasting has increased manifolds from the past two decades. Due to variation in weather changes, significant problems came across in the supply and demand of electricity. Therefore, predictive models are utilized and employed to combat this problem. In this paper, medium-term wind speed is predicted using BNN and LASSO. The data is obtained by the NWP model, which usually forecasts the weather parameters. The key objective of predicting the wind speed is to eliminate the errors between predicted and actual wind speed using BNN. The performance indices used for measuring the accuracy are MAPE and NMAE. The result shows that BNN has outperformed exceptionally well and attained good accuracy for 6 to 72 hours ahead of prediction by the estimation forecasting as compare to LASSO which didn’t provide good accuracy at any hour. Extensive research has been carried out in wind speed forecasting using different machine learning approaches, and still, there is always room for improvement. Additionally, the proposed predictive model seems to be useful for wind speed forecasting for longer time horizons.

In prospects, machine learning techniques have a wide range of algorithms for improving prediction performance. Firstly, BNN can do long-term wind speed forecasting on a broader time horizon. Secondly, the hybridization of different linear and non-linear can also be utilized for wind speed prediction (Babbar & Lau, 2020). In last decade there has been research on combining techniques for prediction purposes, and BNN is observed promising for the ensemble approach. But the small gap has been observed in attaining high accuracy due to the limitation of data set. Lastly, the proposed BNN model can also be applied to other energy forecasting domains, such as solar power forecasting, planning and optimization of the electric grid, and load forecasting.

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