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Wind Power Prediction Using Neural Networks with Different Training Models

Sana Mohsin Babbar[1], Tameer Hussain Langah[2]
[1]Asia Pacific University of Technology and Innovation, Kuala Lumpur, Malaysia
[2]Faculty of Engineering, QUEST, Nawabshah, Pakistan
Corresponding Author: Sana Mohsin Babbar; Email: sana.mohsin11@gmail.com

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ABSTRACT

Energy in any form is a vital source of producing electricity for daily utilization. Wind energy source as renewable energy is playing a pivotal role in generating power from electric gird owing to environmentally friendly feature. Due to the volatile and intermittent nature of wind energy, fluctuations and disparities occur in installing, monitoring, and planning in an energy management system. Therefore, forecasting and prediction are promising solutions to address mismanagement at the grid. Consequently, machine learning tools specifically neural networks have created a huge impact in forecasting wind power. In this study, the feed-forward neural network is adopted for predicting wind power. Additionally, for having precise and efficient results, different training models i.e. one-step sacent, resilient propagation, Bayesian regularization, scaled-conjugate gradient back propagations, and Levenberg-Marquardt are used to make the comparative analysis. From the simulations and results, it was concluded that Bayesian regularization training model is performing best and achieving high accuracy by obtaining 1.66 of RMSE and 6.06 of %MAPE. Eventually, it is concluded that neural networks can be a good choice to predict wind power for optimal solutions. Moreover, the proposed model can be applied to other renewable energy source predictions.

INTRODUCTION

Utilizing electricity from non-conventional sources like wind, solar and biomass has been widely adopted and seems to be a reliable source. Wind energy is the fastest and emerging source globally as it has produced 591 GW in 2018 (Nazir, et al., 2019). For depleting the fossil fuels generated electricity which causes severe environmental issues, the World is in dire need to produce clean energy. Wind energy as the second-largest renewable source is generating power with low maintenance, low cost, and less pollution. The proffering of electricity using wind power strategies is an essential and beneficial replacement for non-renewable sources. On the other hand, disparities and fluctuations have also been observed by utilizing electricity from wind energy. Due to the unpredictable nature and weather conditions, disparities and fluctuations occur while producing and trading electricity (Ogundiran, 2018).

For having an efficient energy management system, forecasting plays an important role. Predicting weather parameters such as wind speed, power, humidity, temperature, solar irradiance, etc. has brought significant solutions to diurnal problems such as trading, maintaining, controlling, and optimization of the electric grid. Therefore, numerous forecasting mechanisms have been brought to the limelight (Lahouar, 2017). Meteorological conditions have gained immense influence on producing energy. Forecasted wind power and speed determine the composition of wind energy produced, renewed at every time step. Efficient and precise predicted wind power brings optimal solutions to grid integration (Li, 2018). Different strategies have been made for predicting wind power on time in different ranges. Mainly, three-time ranges are adopted on the basis of range. Short term wind power is traditionally used and adopted for storage purpose and electricity market, it typically ranges from a few minutes to 6 hours (Li L. L., 2020). When the range expands, prediction becomes tricky and hard to handle. As the range increase from 6 to 72 hours, it is termed as a medium-term wind power forecasting. It is usually used as planning and management of a smart grid. While, when range increases up to days it is called as long-term forecasting which is rarely embraced in past studies (Sharadga, 2020).

Numerous work has been done in the field of forecasting. Wind power forecasting has been seen as the need of the hour in the domain of energy production. In (Demolli, 2019), wind power has been forecasted with different machine learning models according to their nature. The models were chosen according to the data set concerning historical meteorological data. The Least Absolute Shrinkage and Selection Operator (LASSO), XGBoost, k-neighbourhood Neural Network (kNN) regression, and Support Vector Regression (SVR) is used to predict the wind power. The comparative analysis shows that except LASSO, all other machine learning tools are enough efficient to predict accurately. Immense research has been done for predicting wind power by employing neural networks. Studies have also shown that any kind of neural network can bring the best prediction results. In 2017, research was conducted by training the wind power data by adopting Bayesian neural network. The results show Bayesian neural network shows good accuracy almost like other superior neural networks (Mbuvha, 2017). Furthermore, a systematic literature review survey was also conducted in 2019 for knowing adaption of Artificial Neural Networks. 4 research questions and 37 surveys were taken and it was observed keenly that neural networks have a higher rate of usage for predicting wind power as compared to other machine learning models (Maldonado-Correa, 2021).

In addition, as stated in (López, June 2020), a comparison of Echo state network (ECN) and Long term short memory (LSTM) is made for predicting the wind power. In this study, the author later showed that a combination of ECN and LSTM can bring high accuracy and outperforms best. In recent years, a study was conducted on medium-term wind power forecasting by using butterfly optimization algorithm (BOA) and later combined with SVR for final results. The proposed model performed well on time series data (Chen, 2020). In (Li L. Z., 2020), support vector machines (SVM) with dragon optimization algorithm (DOA) was used for short-term wind power forecasting.

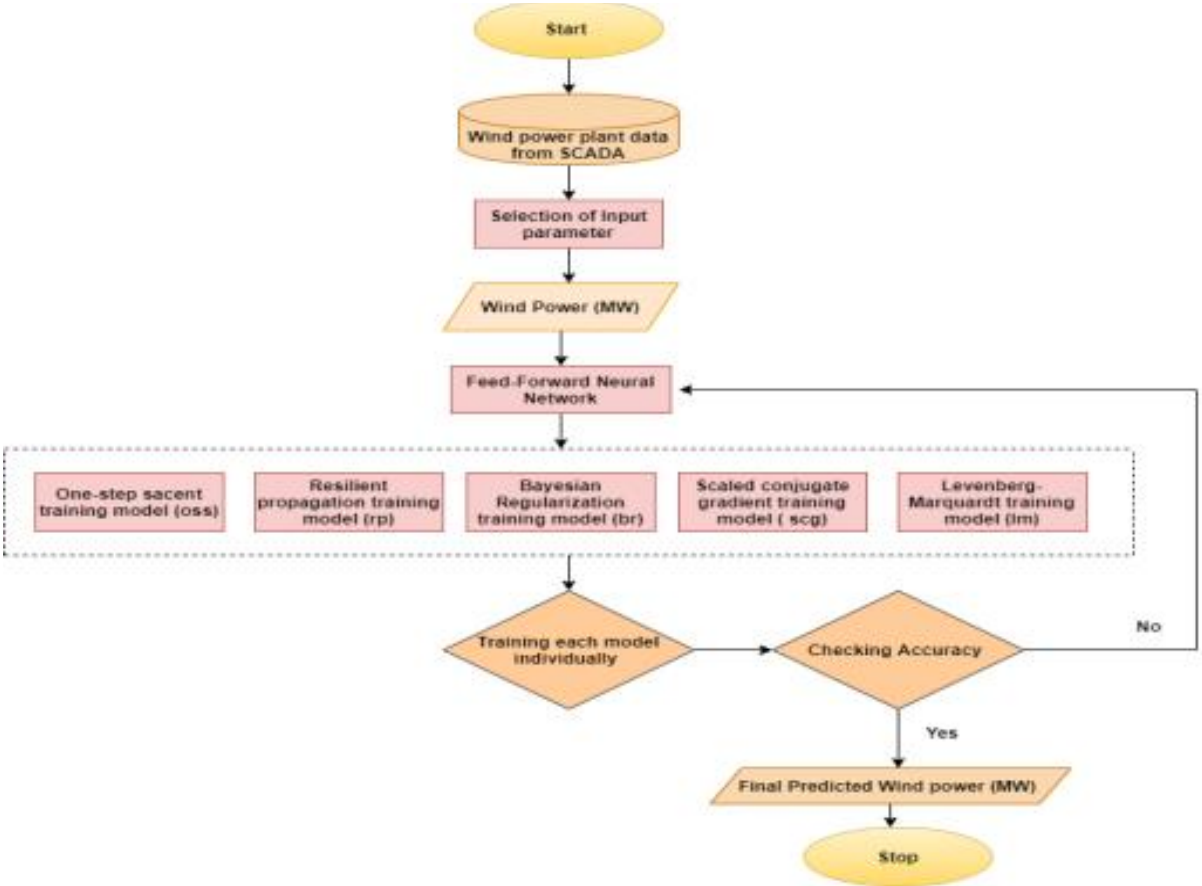
By the results and discussions, it was examined that a combination of DOA and SVM shows better prediction as compared to other backpropagation neural networks and regression models. On the other hand, linear models i.e. regression, random forest, and Kalman filtering are also widely used to predict the wind parameters (Hur, 2021). Studies have also shown that the combination of machine learning algorithms shows good and high accuracy. In (Babbar, 2020), it was discussed briefly that the amalgamation of linear and non-linear machine learning models can bring a huge difference in estimation. The combination of the feed-forward neural network, SVM, and regression has bought good accuracy in predicting the wind speed with the numerical weather prediction (NWP) model's data set (Jahangir, 2020).

However, in this research, different training models are used and compared with each other in terms of their performance. The feed-forward neural network is adopted with five training models to examine which performs better. One-step sacent (oss), resilient propagation (rp), Bayesian regularization (br), scaled-conjugate gradient back propagations (scg), and Levenberg-Marquardt (lm). It was observed that all of them were giving high accuracy with minimal differences. From the quantifying measures, Bayesian regularization is minimizing the errors at its best as compared to other training models.

METHODS

In this study, different training models are adopted in the feed-forward neural network. Assessing and pre-processing data is a foremost step of training any model in machine learning approaches. Raw data of different wind parameters were obtained from a wind power plant. The data was captured by a SCADA system. Later then, wind power was sifted from the raw excel sheets as an input. 900-time steps were taken for the training purpose for one month i.e. almost 40 wind power (MW) instances each day. Data is divided between three divisions. 70 percent of data is dedicated to training purposes while 15 percent is for testing and 15 percent for validation purposes. A feed-forward neural network with 10 hidden layers is chosen as a machine learning model for predicting wind power for the purpose of short-term forecasting. Five different training model are chosen as shown in Figure 1 are trained, tested, and validated with the same input for comparing the performance.

Figure 1. Flow chart of the Proposed Methodology



Individually, every model's accuracy has been checked by the RMSE and %MAPE criterion. It was highly observed that each model is performing with good and high accuracy, the difference in efficacy is very minimal. Hence, the final predicted wind power is obtained after validation of 15 percent of data.

RESULTS AND DISCUSSION

Feed forward neural network (FFNN) is one of the most popular and commutual neural network since decades. It is one of the simplest machine learning tools with a high effective rate. FFNN contains three layers i.e. input layer, hidden layer, and output layer as shown in Figure 1. The input layer contains the input parameter i.e. wind power, wind speed, temperature, humidity, etc. In this study, wind power is chosen as an input to the neural network. Later, the hidden layers work for producing the target. Target plays the role of catalyst between the input and the output layer. Then, the output layer contains the predicted result i.e. predicted wind power. The mathematical expression of the feed-forward neural network is expressed below in Equations 1 and 2.

$$y_k = b_k + x_1 w_1 + x_2 w_{2+\cdots\ldots\ldots+} x_n w_n \quad (1)$$

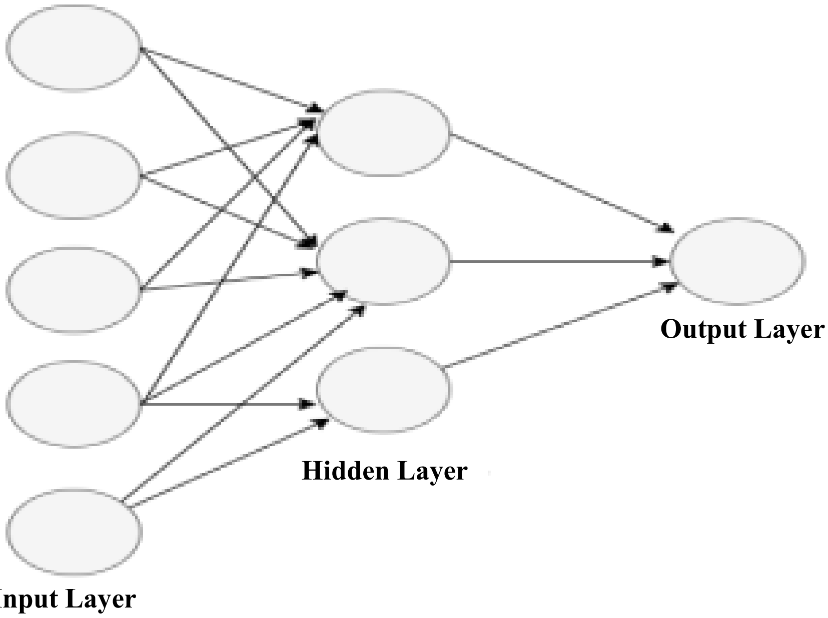
$$v_k = \emptyset(y_k) \quad (2)$$

Where ***yk*** is the final predicted output, ***bk*** are the biases between input and output, ***xn*** are the input neurons and ***vk*** is the activation function to boost up the neural network. However, studies have shown that different training models can be used (Kriegeskorte, 2019). In this research, five different models are trained and compared with each other to check the accuracy. One-step-sacent, resilient propagation, Bayesian regularization, scaled-conjugate gradient back propagations, and Levenberg-Marquardt are used to make the comparative research. Below is Table 1 show, which illustrates the function of these training models:

Table 1. Training Models and their Function

Training Models	Function
One-step sacent	to bridge the gap between input and target
Resilient propagation	Compression of an infinite input to the finite output range
Bayesian Regularization	Minimize a linear combination of errors and weights
Scaled- Conjugate gradient backpropagation	Use to calculate derivates of performance
Levenberg-Marquardt	Supports training with validation and testing

Figure 2. The architecture of Feed-Forward Neural Network



In this section Root Mean Square Error (RMSE) and Percentage Mean Absolute Percentage Error (%MAPE) are chosen for observing the performance. The accuracy of prediction is often checked by two ways. First by checking the trend between target and output but it gets hard to see the exact numbers. Secondly, by performance evaluators i.e. RMSE and %MAPE, the efficacy is seen. According to the %MAPE criterion, if the percentage comes under 10 percent, the accuracy is high otherwise good. According to Figure 3 and Table 2, moving from left to right, RMSE of each model is almost the same. If minute details are seen then Bayesian regularization has minimized errors at its best. By the %MAPE, resilient propagation is showing 10% of accuracy while Bayesian regularization shows 5.8%, which caters that from both evaluators Bayesian regularization has minimized the errors at its possible. From the simulations and results, it is observed that each training model is performing very well with high precisions but Bayesian regularizations show perfection and high accuracy.

Figure 1. Histogram of Quantifying Measures Showing RSME and %MAPE with Training Models

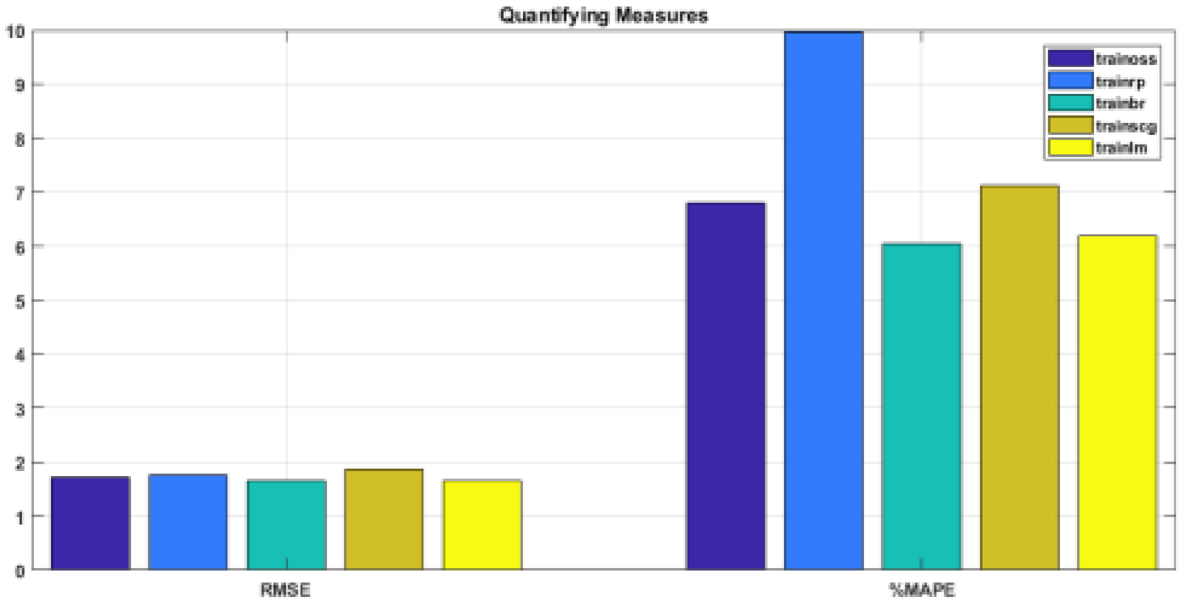


Table 2. Quantifying Measures of Different Training Models

Training models	RMSE	%MAPE
trainoss	1.72	6.80
trainrp	1.76	9.97
trainbr	1.66	6.05
trainscg	1.87	7.12
trainlm	1.66	6.20

Table 2 demonstrates the statistical analysis for analyzing the performance of proposed training models. The facts and figures, it is showing that all the models are good in their performance. From the latent perspective, Bayesian regularization has minimized the errors at its best. While resilient propagation is the last in the comparison. Constructively, it can be easily observed that training models driven by the feed-forward neural network are positively showing good accuracy. For having the minute precision in forecasting the wind parameters, Bayesian regularization is the best tool to gain high efficacy.

CONCLUSION

Paradoxically, predicting wind power is a promising solution to the intermittent nature of wind energy. In this study, different training models featured in feed-forward neural networks were compared with each other. The results and discussion shows that Bayesian regularization gives high accuracy in terms of minimizing errors. On the other hand, it was observed that other models were also showing good accuracy by the percentage MAPE criterion. Furthermore, it is also suggested for the future prospect that the proposed model can be used for other purposes such as load forecasting, solar power, energy management, etc.

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