Neural Network Ensemble for Medium Term Forecast of Wind Power Generation: A Review

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*Abstract***:** *In recent years, environmental considerations have prompted the use of wind power as a renewable energy resource. Wind energy is considered one of the fastest growing renewables. However, the biggest challenge in integrating wind power into the electric grid is its intermittency. One approach to deal with wind intermittency is forecasting future values of wind power production. Improved wind forecasting is known as an efficient tool to overcome many problems. For example, when it comes to competitive electricity markets, accurate wind forecast is always alluring for a variety of reasons. Thus, several wind power or wind speed forecasting methods have been reported in the literature over the past few years in order to improve the forecast accuracy. Hence, this paper offers a review on wind power forecasting and focuses on more on the state-of-the-art artificial neural network techniques. The review explores existing gap in recent studies and suggest future research opportunities in the context of wind power forecasting.*

Keyword: *Artificial Neural Network, Ensemble technique, Recurrent Neural Network, Deep Learning and Deep Recurrent neural Network*

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1. INTRODUCTION

Wind energy is one of the renewable energy sources characterized by the lowest cost of electricity production and has experienced a significant expansion in installed capacity in recent years. A study shows that with wind energy, 12% of all electricity generation may be achieved through wind power by 2020(G. Chang, Lu, Hsu, & Chen, 2016). Intelligent management and application of renewable energy can alleviate pressure on energy demand. Wind energy is a vital source of renewable energy with large reserves and wide distribution(Liu, Chen, Lv, Wu, & Liu, 2019). In recent years, environmental considerations have prompted the use of wind power as a renewable energy resource. Wind energy is considered one of the fastest growing renewables.
green energy resources in the world, especially in the USA, Europe, Canada, India, and Africa. Wind energy has been an important part of the electricity markets in every country around the world because it offers many advantages, including clean green energy and low prices, and it does not produce emissions that cause acid rain or greenhouse gases. Precise forecasting of wind power is imperative for an efficient and economical integration of wind energy into the electricity supply system. The wind power produced by a wind farm critically depends on the stochastic nature of the wind speed, and unexpected variations in the wind power output increase the operational cost of the electricity system(Q. Zhou, Wang, & Zhang, 2019).
However, the biggest challenge in integrating wind power into the electric grid is its intermittency. One approach to deal with wind intermittency is forecasting future values of wind power production. According to Mocanu et al. (Mocanu, Nguyen, Gibescu, & Kling, 2016), forecasting can be grouped into either one of these three groups, they include (i) short term forecast usually ranging from day-week (ii) medium term forecast usually ranging from week-year and (iii) long-term forecast usually ranging from year and above. Thus, several wind power or wind speed forecasting methods have been reported in the literature over the past few years in order to improve the forecast accuracy (Soman, Zareipour, Malik, & Mandal, 2010).

These method as presented by (Hong & Riofiorido, 2019) are: Physical methods which include numerical weather prediction (NWP). NWP uses hydro- and thermo-dynamic models of the atmosphere to predict weather, considering initial values and boundary conditions. In case that accuracy of NWP is poor, the wind power generation forecasting becomes inaccurate. The Statistical methods include probability mass bias, probabilistic auto-regression, vector autoregressive model, and Bayesian framework. These methods concern the relationship between wind power generation and explanatory variables. The Traditional artificial neural networks (ANN) are used for predicting wind power; they include the multi-feed-forward neural network (MFNN), the Radial Basis Function Neural Network (RBFNN)(G. Chang et al., 2016), the wavelet neural network (WNN), the extreme learning machine (ELM) (J. Zhou, Yu, & Jin, 2018) and Elman recurrent neural network(J. Wang, Zhang, Li, Wang, & Dang, 2014). The advantage of these methods is that they require no predefined mathematical model. Hybrid and ensemble intelligent systems, such as combination of ANN and fuzzy logic system, have also been used for forecasting wind power generation recently. ANN and fuzzy logic system can compensate each other to achieve a fair forecasting, and also the Deep learning neural networks have begun to have an impact on the study of forecasting. Commonly used methods in the networks are auto-encoders, long-short-term memory (LSTM)(Fu, Hu, Tang, Yu, & Liu, 2018), the restricted Boltzmann machine (RBM)(Santhosh, Venkaiah, & Kumar, 2019) and the convolutional neural network (CNN) (Hong & Riofiorido, 2019). Compared with the traditional ANNs, deep learning neural networks do not need extra unsupervised networks or data (signal) preprocessing (e.g., decomposition). Deep learning neural networks outperform the traditional neural network in the renewable power forecasting problems.
On the other hand, ensemble models have also attained global attention in recent years. Nowadays, around 90% of the developed wind speed and power forecasting approaches are ensemble models. These hybrid models can be implemented by combining the superior features of the individual models. In general hybrid models have proof to achieve high accuracy particularly short-term forecast an hour (Qing & Niu, 2018) to a week (Iwafune, Yagita, Ikegami, & Ogimoto, 2014). But there are few limited work pertaining medium to long term prediction with previous work showing errors in excess of 40-50% as regard to medium to long term forecasting (Yun, Luck, Mago, & Cho, 2012).

1.2 Advantage and Motivation

Forecasting of wind speed and wind power generation is indispensable for the effective operation of a wind farm and the optimal management of revenue and risks. Improved wind forecasting is known as an efficient tool to overcome many problems. For example, when it comes to competitive electricity markets, accurate wind forecast is always alluring for a variety of reasons. Firstly, appropriate incentives of attractive market price are offered on energy imbalance charges based on market price. Secondly, a correct forecast can help to develop well-functioning hour ahead or day-ahead markets.
The future values of wind power generation comprehend three different time horizons: short, medium and long-term. Short-term forecasts are mainly useful for operational purposes (i.e., economic load dispatch planning, load increase/decrease decisions), while medium-term forecasts aim to increase operational security of day-ahead electricity markets and corroborate
online/offline decisions. Finally, long-term forecasts provide information for power system risk assessment and also to identify potential for wind power generation in specific areas, providing valuable data for energy planners (Vargas et al., 2019).

2. RELATED WORK

According to Mocanu et al. (Mocanu et al., 2016), forecasting can be grouped into either one of these three groups, they include (i) short term forecast usually ranging from day-week (ii) medium term forecast usually ranging from week-year and (iii) long-term forecast usually ranging from year and above. Thus, several wind power or wind speed forecasting methods have been reported in the literature over the past few years in order to improve the forecast accuracy (Soman et al., 2010). For example (Pousinho, Catalao, & Mendes, 2010) proposed particle swarm optimization and adaptive-network-based fuzzy inference and compare the results with ARIMA and NN approaches, the HPA approach presents enhanced forecasting accuracy, although the results only validate the proficiency of the proposed approach in short-term wind
power prediction. Similarly, (G. Chang et al., 2016) proposed a hybrid ARIMA-NN model to increase the forecasting accuracy of wind speed and wind power and evaluate the performance against ARIMA, BPNN, RBFNN, the results show that the forecast accuracy of the proposed

model is relatively superior to the other three models while the computational efficiency is maintained. Also, (Heinermann & Kramer, 2014) propose support vector regression ensembles and evaluate the performance with KNN and SVR SVR experimental results demonstrate that ensemble approach renders significantly better forecast results than state-of-the-art predictors

One of the common limitations among statistical, engineering and hybrid models is the availability of vital data (Robinson et al., 2017). There have been limited number of work with regard to medium and long term forecasting either sub-hourly or hourly-intervals with long term prediction being more difficult and complex task to achieve, a relative error often in excess of 40-50 % is associated with medium to long term forecasting (Mocanu et al., 2016). Potential improvement on prediction accuracy of the aforementioned machine learning can be obtained using deep neural network where modeling of more complex functioning is allowed by the use of several layers of abstraction (24). These approaches are applied recently in the context of energy prediction for example, (Fu et al., 2018) presents a novel multi-step ahead wind power prediction model based on recurrent neural network (RNN) with long short-term memory (LSTM) unit or gated recurrent unit (GRU), the model performance was evaluated against ARIMA method and SVM in which RNN approaches was found to be superior in performance. Similarly, (Hong & Rioflorido, 2019) proposed hybrid deep learning neural network for 24 h-ahead wind power generation forecasting, the proposed CNN is more accurate than traditional methods for 24 h-ahead wind power forecasting. In general ensemble and hybrid method have shown to achieved very high accuracy in the context of wind forecasting and have been the most proposed technique recently when compare to tradition or individual models. The table below provide the summary of various computational techniques that were apply in the context of wind speed and wind power forecasting.

Table 1 Summary of related works by Proposed System, Method Compared, Strength, Weakness and Limitations

Reference	**Proposed Method**	**Compared Algorithm**	**Findings**	**Weakness**
(Pousinho, Catalao, & Mendes, 2010)	particle swarm optimization and adaptive-network-based fuzzy inference	ARIMA and NN approaches	HPA approach presents enhanced forecasting accuracy	The results only validate the proficiency of the proposed approach in short-term wind power prediction
(Heinermann & Kramer, 2014)	support vector regression ensembles	*k*NN and SVR	SVR ensemble approach renders significantly better forecast results than state-of-the-art predictors	Analysis of other methods for optimization and diversification of the weak predictors in order to improve the prediction performance
(J. Wang et al., 2014)	Hybrid of empirical mode decomposition (EMD) and Elman neural network (ENN)	persistent model, back-propagation neural network, and ENN	EMD–ENN model consistently has the minimum statistical error	Computational complexity
(Cadenas, Rivera, Campos-Amezcua, & Heard, 2016)	ARIMA and NARX	Univariate ARIMA Model and a Multivariate NARX Model	multivariate NARX model produce more accurate results	Outliers may affect prediction performance
(G. Chang et al., 2016)	hybrid ARIMA-NN model to increase the forecasting accuracy of wind	ARIMA, BPNN, RBFNN	forecast accuracy of the proposed models is relatively superior to the other three models	High computational time

	speed and wind power		while the computational efficiency is maintained	
(Han, Meng, Hu, & Chu, 2017)	non-parametric hybrid models for probabilistic wind speed forecasting	BP, SVM and RF models	NP based hybrid models generally outperform the other models and have more robust forecast performances	Complex to implement
(Cao, Wang, Huang, Luo, & Wang)	A novel transfer learning strategy for short-term wind power forecasting	Support Vector Machines (SVM), and Least Absolute Shrinkage and Selection Operator (LASSO) and Neural Networks	Jaya-XGBoost algorithm yields the best results over the four algorithms	the result the forecasting performance degraded with the increasing of forecasting horizons
(Huang & Kuo, 2018)	convolutional neural network algorithm for short-term forecasting	SVM, RF, DT, and MLP	That WindNet (CNN) achieves the most efficient results in both RMSE and MAE	Not suitable for time series forecasting
(Fu et al., 2018)	a novel multi-step ahead wind power prediction model based on recurrent neural network (RNN) with long short-term memory (LSTM) unit or gated recurrent unit (GRU)	ARIMA method and SVM	RNN approaches was superior in performance	Missing Data
(Serttas, Hocaoglu, & Akarslan, 2018)	Mycielski-Markov is utilized to forecast solar power generation	Mycielski signal processing technique and probabilistic Markov chain	Mycielski-Markov model provides very successful results in forecasting of solar power	Determining the optimal number of states should be considered
(J. Zhou et al., 2018)	ESMD-PSO-ELM model	BPNN, ELM, PSO-ELM	The empirical study demonstrates that the proposed model is more robust and accurate in forecasting short-term	May suffer from Over fitting
(Yuan, Qian, Jing, & Pei, 2018)	Least Squares Support Vector Machine (LSSVM) and State Transition method	Persistence, Autoregressive Integrated Moving Average (ARIMA), Back-Propagation	ST-LSSVM hybrid model has the best prediction accuracy in one to six step's	if the prediction results of the previous steps are poor, the overall performance of

	(ST). In order to further enhance the model performance, Particle Swarm Optimization (PSO)	Neutral Network (BPNN) and Least Squares Support Vector Machine (LSSVM) models	forecasting	proposed ST-LSSVM hybrid model will be significantly reduced, it needs to be improved in further research
(Q. Zhou et al., 2019)	Hybrid forecasting system based on an optimal model selection strategy for different wind speed forecasting problems	GABPNN, PSOBPNN, GAPSOBPNN	proposed approach is effective, and can achieve a better forecasting accuracy in comparison with a single ANN	For long-term wind speed forecasting, only MOGAPSO-BPNN and MOGAPSO-ANFIS are suitable for wind speed time series forecasting
(Hong & Rioflorido, 2019)	hybrid deep learning neural network for 24 h-ahead wind power generation forecasting	CNN-MFNN and CNN-RBFNN	the proposed method is more accurate than traditional methods for 24 h-ahead wind power forecasting	Requires algorithm that can eliminate the negative influence of outliers and the presence of spurious data on forecasting performance
(Du, Wang, Yang, & Niu, 2019)	Propose a novel hybrid forecasting model based on multi-objective optimization	ARIMA, Persistence model, GRNN, WNN, LSSVM	The proposed hybrid model demonstrates higher prediction accuracy and reliability	High Computational Time
(Jiang & Liu, 2019)	Variable weights combined model based on multi-objective optimization for short-term wind speed forecasting	ARIMA, BP and ENN	proposed model surpasses the contrasted benchmark models and is satisfactory for intellective grid programs	the developed model is not perfectly efficient in all situations and applications
(Begam & Deepa, 2019)	Optimized nonlinear neural network architectural models for multistep wind speed forecasting	ARIMA, BPNN, MLPN, FFNN, EN and SVM	shows better performance than the other models considered for comparison	wind-speed time series data for the target sites were considered only for 10-min
(Zhang, Chen, Pan, & Zhao, 2019)	A novel hybrid model based on VMD-WT and PCA-BP-RBF neural network for short-term wind speed forecasting	RBF, PCA-BP-RBF, EMD-PCA-BP-RBF	greatly improved the accuracy in short-term wind speed forecasting	there is no better method to determine the mode number of VMD
(Demolli, Dokuz, Ecemis, & Gokcek, 2019)	Wind power forecasting based on daily wind speed data using machine	LASSO, ENN, KNN, SVR, RF and XG-Boost	This study demonstrated that machine learning algorithms could be	Over fitting Prroblems

	learning algorithms		successfully used before the establishment of wind plants in an unknown geographical location whether it is logical by using the model of a base location	
(Ding et al., 2019)	A gated recurrent unit neural networks-based wind speed error correction model for short-term wind power forecasting	SVM and ANN	the proposed model outperforms these benchmark models	Accuracy is Limited to short term
(Wu, Wang, Chen, Du, & Yang, 2020)	A novel hybrid system based on multi-objective optimization for wind speed forecasting	GRNN, ENN, BPNN, ELM, ARIMA and persistence	the proposed system achieves superior accuracy and stability than the compared models	Not applicable to other related fields
(G. Wang, Jia, Liu, & Zhang, 2019)	A hybrid wind power forecasting approach based on Bayesian model averaging and ensemble learning	BPNN, SVM, RBFNN and BMA-EL	accurately and reliably forecast the wind power outputs under different meteorological conditions, with higher precision and reliability	Complex to implement
(Qu, Mao, Zhang, Zhang, & Li, 2019)	Multi-step wind speed forecasting based on a hybrid decomposition technique and an improved back-propagation neural network	RBF ELM EEMD-GA-BP WPD-PSO-GRNN CEEMDAN-EWT-FPA-BP	the proposed model is highly suitable for non-stationary multi-step wind speed forecasting.	Lacks generalization
(Santhosh et al., 2019)	Short-term wind speed forecasting approach using Ensemble Empirical Mode Decomposition and Deep Boltzmann Machine	Persistence model, BPNN, ENN, SVR and DBM	the proposed deep learning strategy is found to give more accurate results in comparison with existing approaches	The number of hidden layers in the network can be increased for better extraction of time-series features
(Xiang, Deng, & Hu, 2019)	Forecasting Short-Term Wind Speed Based on IEWT-LSSVM Model Optimized by Bird Swarm Algorithm	LSSVM-BSA, EMD-LSSVM-BSA, EWT-LSSVM-BSA, VMD-LSSVM-BSA	the presented hybrid forecasting model can effectively follow the change of wind speed, which exhibits more superior predicting	Performance is limited to short term prediction

			performance than other popular models	

3. DISCUSSION, CHALLENGES AND RECOMMENDATIONS

A lot of effort is being employed in the context of wind speed and wind power forecasting due to the relevancies of the information for planning. Various approaches have been applied as discussed in the literature. Based on our survey, it is obvious that hybrid and ensemble learners has shown to excel other predictions approach in terms of accuracy. Although all predictions method discussed in the literature comes with a weakness, it's all depends on the approach one may decide to use. For easy identification of the type of prediction model to use, we provide a table for the comparison of various prediction methods. Forecasting method such as linear models, which were relegated due to their limitation in solving nonlinear problem are found to be still relevant in the context of energy predictions. Ensemble and Hybrid Models are suitable for solving nonlinear problem with high accuracy of predictions and are currently employ in the context of wind speed and wind power forecasting due to their abilities to model complex function with high accuracy. The work pertaining medium to long term prediction is few, this is because of the complexity associated with the forecasting, liable to produce high error. There are various challenges associated with the prediction of wind speed and power forecasting which leave open issues to be address by researchers as presented in the literature. Based on our review, we identify some open issues and thus drive the following recommendations:

I. Outliers is an important factor that mitigates the prediction accuracy, further research should focus on eliminating the negative influence of outliers and the presence of spurious data on forecasting performance on wind power forecasting

II. Given the high accuracy and effectiveness of intelligent predictors, they currently play the primary role in the field of wind energy forecasting. But the models relying only on historical data are still not convincible enough. More prior knowledge or problem-focused perfection are required to improve their ability further. Besides, the background of massive experiential knowledge may be able to make the intelligent predictors more powerful Future research should focus on tackling the problem of missing data imputation scheme in order to improve the prediction accuracy,

III. Ensemble and hybrid technique which have shown to provide reliable and better results still surfers due to their implementation and computational complexity, more research should be done to bridge this gap with simpler but effective models.

IV. Deep recurrent neural network such as long short-term memory gated recurrent unit and Elman neural network looks promising in forecasting wind speed and wind power with high accuracy, future work should capture the aforementioned outliers that mitigate the prediction accuracy in the models.

V. Robustness of predictor need to be improved upon since the process of collecting wind speed data and signal transmission makes the obtained dataset inevitably contain a small amount of noise. To solve this problem, models that are robust to outliers can be utilized, such as robust KF [10], SVR with robust loss function. The robustness improves the ability of the model to process different samples and noise.

VI. Adaptiveness of hybrid forecasting model need to be further research: The forecasting models need to target a large number of wind farms. Building a model for each wind farm is time-consuming and unnecessary. In order to obtain better universality, the forecasting model should not be limited to a fixed mode. This can be achieved by using transfer learning

VII. Few works focus on long-term forecasting due to error associated with this type of forecasting, future work should focus on improving long term forecast accuracy using the aforementioned computational techniques.

4. CONCLUSIONS

Wind energy is one of the renewable energy sources characterized by the lowest cost of electricity production and has experienced a significant expansion in installed capacity in recent years. Wind energy is a vital source of renewable energy with large reserves and wide distribution However, the biggest challenge in integrating wind power into the electric grid is its intermittency. One approach to deal with wind intermittency is forecasting future values of wind power production. Thus, new automated paradigms have to be thought so as to improve the forecasting performance of wind speed and wind power. This paper reviews the various approach, focusing on hybrid and ensemble deep learning towards solving these problems. Recently hybrid and ensemble techniques have been successfully applied to this context. From our review, it obvious that hybrid and ensemble adoption in predicting time series with dynamic behavior as an alternative to conventional method due to their ability to learn complex function and self-adoption to any models. Various prediction algorithms base on hybrid and ensemble learners were presented in this review and the weaknesses associated to each method were identified to enable future researchers know arrears that require more attention in the future. The review can help researcher to identify areas that needs future advancement quickly and develop a novel approach to wind speed and wind power forecasting in wind farms.

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