A Review On The Hybrid Approaches For Wind Speed Forecasting

S.Vidya, Dr.E.Srie Vidhya Janani

Abstract: Wind power is one of the important generation technologies in today's world. The generation of wind power mainly depends on wind speed. The wind power generation availability for the grid is determined by the number of wind speed forecasting techniques. One of the main difficulties is variability and unpredictability of wind speed. There are several issues in the integration of wind energy into the power system. The relevant issues can be overcome by having accurate wind speed forecasting tools. This paper outlines the bibliographical survey on various approaches of wind speed forecasting. In addition, various metrics to assess the forecasting error are discussed. The researchers who are working in this area of research can make use of this survey. The wind farm owners can understand the current wind prediction models by this survey.

Index terms: Auto Regressive Integrated Moving Average, Artificial Neural Networks, Fuzzy Logic Systems, Genetic Algorithms, Numerical Weather Prediction, Support Vector Regression, Wind Speed Forecasting.

1. INTRODUCTION

Renewable energy has attracted the people due to the depletion in the conventional resources. In the world, one of the fastest growing powers is wind power. The goals of sustainability and security of supply have to be achieved in the integration of wind power in the power system [1]. The increase in the wind power is due to the environmental concern over fossil fuels, decreased cost and improved technology [2]. Burning of fossil fuels causes acid rain, oil spills, decreased biodiversity and increase in greenhouse gases and urban pollution. The most promising alternatives are renewable resources [3]. The advantages of wind energy over other renewable sources are (1) Wind energy has low maintenance (2) Polluting waste is not produced. (3)Throughout day and night energy is produced by wind (4)The power generation is in large scale, when compared to other systems. (5)Wind is an inexhaustible resource. Predicting the wind for power generation is different when compared to predicting the wind for weather stations. The optimal management of electricity grids depends upon the prediction of wind power. Wind power generation depends upon wind speed. Wind turbines are installed at the highest possible heights from the ground because wind speed will be greater for the regions which have more height from the ground. In air traffic control and satellite launch, ship navigation and missile guidance, wind speed forecasting is already in use for many years [4]. To predict local grid congestion, grid operators use forecasts and energy traders use forecasts for spot prices [5].

- *S.Vidya is currently working as Assistant Professor, Department of CSE, Kalasalingam Institute of Technology, Krishnankoil – 626126, TamilNadu, India. E-mail: vidya.lkshm@gmail.com*
- *Dr.E.Srie Vidhya Janani is Head of Department , Department of CSE, Anna University, Madurai Regional Campus, Madurai-625019, TamilNadu, India. E-mail: esrievidhya@gmail.com*

The wind will be originated due to the uneven heating of the sun on the earth's surface [6]. There are many complex events which influence the behaviour of the wind [7]. Due to the intermittency and variability characteristics of wind, wind speed forecasting is an unique challenge. The improvements in the wind speed forecasting are done by taking extensive efforts. Short term wind predictions ranging from minutes to few days are focused recently. Scheduling and unit commitment are the important system operations in day-ahead predictions [8],[9]. Wind speed forecasting techniques can be categorized based on forecasting horizon. In order to have accurate short term forecasting, traditional methods such as Numerical Weather Prediction (NWP) can be used with several prediction hours. Very short term prediction such as several minutes to hours can be done by persistence method. The satisfactory results cannot be obtained by individual models in wind speed forecasting. Advanced forecasting methods can be obtained by using hybrid models for higher accuracy levels. Novel forecasting models can be used with high computing power and processing speed. Wind speed can be predicted with some significant errors as per today's status of wind forecasting methods [10]. A comprehensive research has been made by referring to a large number of studies related to wind speed forecasting. This paper aims to describe the most relevant methods of wind speed forecasting which are used in recent years and gives an idea to wind turbine owners to choose the type of wind speed forecasting to be installed in their turbines and to fix price in the intraday markets.

2. APPROACHES OF WIND SPEED FORECASTING METHODS

The wind speed forecasting techniques can be divided into physical methods and statistical methods. The physical parameters such as temperature, local terrain and wind farm layout are taken into consideration by physical method which uses the output from Numerical Weather Prediction (NWP). NWP uses the mathematical model for wind speed forecasting [11]. This model needs supercomputers for large computations and it is suitable for long term predictions [12].

2.1 Classification based on temporal range

Each type of forecasting is important in wind power plants. The temporal range of wind speed prediction is divided into four: very short-term (VT), from a few seconds to one hour; short-term (ST), from one hour to two days; medium-term (MT), from two days to a week ahead; long-term (LT), for forecasting from a week to year or much ahead;Very short term prediction clarifies additional information in the market and is relevant for configuring wind turbines [13]. Short term prediction helps to decide the increment or decrement in power which means economic load dispatch planning. The decision of shutting down wind turbines is made by using the Medium Term prediction [14]. Long Term prediction helps in optimizing the cost in planning the maintenance. A comparison of basic wind speed forecasting approaches is presented in Table 1.

Table 1. *Comparison of various wind speed forecasting approaches*

Approach	Advantages	Disadvantages
NWP models	Longer prediction horizons are suitable	Large computational resource and time is required and not suitable for short time forecasts.
Statistical methods	Basic structure and capable of correcting local trends in data	Non-linear problems are difficult to model and require historical data.
Fuzzy system based models	Less complex and suitable for systems which are difficult to model.	In case of many rules these models take long time.
ANN models	High error tolerant and gains knowledge from training data	Large number of training data and training procedure is needed
SVM based models	Performance is highly generalized.	Training time is longer and the optimization process is complex.
Kalman filter models	Its main feature is recursive form and historical data is not required.	The previous knowledge of the system is required.
Bayesian networks	Small training datasets and the missing values can be easily handled and	More effort is required.

2.2 Statistical Methods

Due to the usage of large computational resources and long operation time of NWP, short time forecasts use the statistical approaches. The statistical approaches describe the relationship between the historical time series of wind speed. They are cheaper, easy to model and good for short time periods. They do not have any pre-defined mathematical model. A versatile and well known algorithm called AutoRegressive (AR) model was developed by Huang and Chalabi [15]. AutoRegressive algorithm is an example for statistical method. Torres et al proposed Auto Regressive Moving Average (ARMA) for longer prediction horizons [16]. According to the Mean Absolute Error (MAE) criterion four competing approaches based on ARMA method for forecasting of wind speed was employed by Ergin and Shi [17]. Autoregressive Integrated Moving Average (ARIMA) was developed for hourly prediction of wind time series by Sfetsos [18]. Kavasseri and Seetharaman developed fractional ARIMA (f-ARIMA) for forecasting upto 48 h which outperforms the persistence model [19]. Erasmo and Wilfrido compared the ARIMA and ANN model to forecast the wind speed of south coast of Oaxaca. When the training vectors of ANN are increased, the performance could be better [20]. Kalman Filters model establishes state-space models and takes wind speed as state variable. It is suitable for online forecasting of wind speed [21].

2.3 Spatial Correlation Models

The spatial correlation models exploit the spatial relationships of neighboring sites to estimate the wind speed. It is very difficult to get the data of neighboring sites. Spatial correlation gives good results in Short Term and Very Short Term prediction. This model is difficult than the Time series model because the data of timely transmission and spatial correlated sites are needed. The wind speed is predicted by employing the wind speed time series of predicted point and its neighboring sites [21]. Damousis et al. designed a method combining spatial correlation and fuzzy method. The dataset of neighboring sites with a radius up to 30km was taken and genetic algorithm is the training method [23]. Based on measured data of another site, Alexiadis et al. proposed Spatial Correlation Predictor (SCP). The model is tested by taking the dataset of 7 years of six cities and it performed well [24]. Focken et al. studied the reduction of the prediction error by using the spatial correlation model. The number of sites and the size of the region decide the reduction of error. The improvement of the power production can be done by having only a few sites [25]. Locally feedback dynamic fuzzy neural network (LF-DFNN) with spatial correlation method for wind speed forecasting was proposed by Barbounis and Theocharis. This model is efficient than other network models [26]. The spatial correlation method is combined with ANN by Bilgili et al. The wind speed of target stations are predicted by the wind speed of reference stations [27].

2.4 Fuzzy System Based Models

Fuzzy logic based approaches use a set of simple rules to model system behaviour. In order to remedy the lacks of learning ability, Artificial Neural Network (ANN) is combined with Fuzzy Logic systems in the prediction of very short term wind speed [28]. The promising results are obtained for wind speed forecasting using Bayesian based methods [29]. Artificial Neural Networks is combined with Fuzzy Logic for wind speed forecasting by Mohammad Monfared et al. This method is efficient than traditional one and takes less computation time [30]. George Sideratos et al presents Erroneous wind speed forecasts which is recognized by a Fuzzy Logic model that uses two Radial Basis Functions (RBF). This model shows more benefits in complex terrain wind farm [31]. Fatih O. Hocaoglu et al proposed Adaptive Neuro Fuzzy Inference system which is used to forecast the missing wind speed data [32]. Adaptive Fuzzy Neural Networks model was designed by Pinsone et al for advanced wind speed forecasting that can be used for long term or short term predictions [33]. Fuzzy model is combined with neural networks by Sideratos and Hatziargyriou and obtained satisfactory forecasting results [34].

2.5 Artificial Intelligence Based Models

Artificial Intelligence Methods provide best results in most situations. ANN has been an efficient forecasting technique as it has easy implementation and self learning feature. It has structure as neural processing in the brain. ANN consists of input layer, output layer and hidden layer. The neurons in one layer are connected to the previous layer and each neuron has transfer function and its own weight [35]. Obtaining the weights of each connection and neurons threshold value is done in the training process [36]. The network error should be minimum. ANN needs shorter development time, simpler to construct and no need of mathematical expressions. ANN can be designed by identifying the correct input, setting up the network structure and then a training algorithm is modelled. The black-box models are ANN and SVM. They are designed from the solution pattern which is in the form of input and output. The techniques such as Support Vector Machine (SVM), K-nearest Neighbors algorithm (KNN) and neural networks describe highly complex statistical relationships between input and output data. Different models based on KNN are designed by Yesilbudak, Sagiroglu and Colak for short term wind speed prediction. Fake neighbors are revealed by this model [37]. The existing ANN models are Radial Basis Functions topology [38], Adaptive Fuzzy-Neural networks [39, 40], multi-layer perceptron [41]. ANN is implemented by Cadenas and Rivera on hourly wind speed time series to enhance prediction accuracy [42]. Three different ANN types, namely, Adaptive Linear Element (ADALINE), Feed Forward Back-Propagation (FFBP) and Radial Basis Function (RBF) are developed for 1-h-ahead wind speed predictions and each model yields different forecast accuracies in terms of various evaluation criteria [43]. MultiLayer Perceptron Neural Network is proposed by Velo, López and Maseda. This model uses one month of data and the results are better [44]. Multilayer perceptron trained by Bayesian Regularization algorithm is proposed by Lopez [45]. Malik and Savita proposed an artificial neural network which takes many input variables for wind speed prediction in 39 sites of Maharashtra [46]. Five different neural network models were implemented for short term forecasting by Kaur, Kumar and Segal on the basis of historical time series. The neural network which has 19 hidden layers, 4 inputs and 1 output performs much better than the other models for short term wind speed forecasting [47]. ANN model which uses back propagation algorithm is proposed by Liang Wu et al for short term wind speed prediction [48]. Yiannis A. Katsigiannis et al presents an ANN model that uses the performance of the neuro-fuzzy model and gives accurate forecasting results [49]. ANN model outperforms AR model which is developed by Mohandes et al [50]. Flores et al. proposed a control algorithm which is based on ANN model using back-propagation method. This model obtains maximum economic benefits [51]. ANN-based network is proposed by Carolin Mabel and Fernandez which has good performance [52]. Recurrent multilayer perception neural network (RMLP) is proposed by Li which uses Kalman filter based back-propagation algorithm as the training method. The method works better for long-term prediction [53]. SVM is an effective tool for non-linear classification problems. Salcedo-Sanz, Ortiz-Garcia, Perez-Bellido, Portilla-Figueras, designed a model based on Multi Layer Perceptron and SVM algorithm for short-term wind speed forecasting by taking the variables such as wind speed, direction, pressure and temperature. In this model, SVM outperformed the Multi Layer Perceptron [54]. SVM models are developed by Lahouar and Slama for short term wind speed prediction. Rapidity and simplicity are the advantages of SVM. Compared to NN models, SVM model using the ERBF kernel had the highest performance for the short term wind speed forecasting [55]. Least Squares SVM (LSSVM) is a reformulation of the SVM problem is developed by Zhou et al for one step ahead wind speed forecasting. Compared to the persistence model, this method gives the reasonable accuracy levels [56]. A support vector classifier is developed by Ji et al. which provides better performance than traditional SVM [57].

2.6 Evolutionary Based Algorithms

The powerful optimization technique is Evolutionary Algorithm (EA). Global optimum solution is achieved with high probability using EA. It is a parallel process which finds optimal solution, when other optimization methods fail. EA is particularly used in evolutionary programming techniques like Particle Swarm Optimization (PSO) and in genetic algorithms (GA).

2.6.1 Genetic Algorithm Based Methods

GA-BP model is developed by Xingpei et al in which the initial weights and bias are optimized by GA. This model is superior when compared to two different BPNN models [58]. GA is combined with grey NN [59]. GA is used to select the optimal parameters of Support Vector Regression [60]. In order to achieve the optimal solution, GA is combined with Least Square Support Vector Machine [61, 62]. In ARMA model, GA is used to select the optimum random number seeds which is proposed by Y. Gao et al. This model is used to simulate hourly wind speeds [63]. Prediction precision can be improved in GA Back propagation method in which GA is used to optimize the structure, bias and weights of BPNN [64]. GA is used to optimize the initial weights of ANN by Guo et al [65].

2.6.2 Particle Swarm Optimization

Extended Kalman filter (EKF) based PSO optimization technique is designed for the training process of RMLP (Recurrent MLP) network model on the basis of minute samples [66]. Richard L et al proposed Recurrent Neural Networks trained with PSO which is used in short term wind speed forecasting [67]. Evolutionary Algorithms and PSO are combined to form the hybrid concept EPSO. PSO method is compared with four methods of wind prediction by Rene Jursa. This group of different models provide a better accuracy for wind prediction [68].

2.7 Hybrid Techniques for wind speed forecasting

Hybrid models consist of one linear and one non-linear model. Improving the prediction performance of wind speed forecasting is the main aim of hybrid approaches [69, 70].

The mean monthly wind speed is predicted by using linear and non-linear model [71]. Compared to AI methods, hybrid structures provide relevant results and good performance. A hybrid structure combining an Autoregressive Integrated Moving Average model and a neural network is proposed by Cadenas e Rivera which has a higher accuracy than the ARIMA and ANN model separately [72]. A new hybrid model which combines seasonal adjustment method (SAM), exponential smoothing method (ESM), and radial basis function neural network (RBFN) by Wang, Zhang, Wang, Han and Kong provides better prediction accuracy [73]. A hybrid model combining SVM model, wavelet transform and genetic algorithm is proposed by Liu, Niu, Wang and Fan which outperforms other hybrid structures and persistence method [74]. Wang, Qin, Zhou and Jiang designed the hybrid models named PMERNN and PAERNN which have the combination of support vector machine, seasonal index adjustment and an Elman recurrent neural network [75]. Fazelpour, Tarashkar, and Rosen proposed four hybrid models namely ANN-PSO, ANFIS, ANN-GA, NN-RBF. Among them the hybrid model PSO gives better accuracy [76]. Hu, Zhang, Yu, and Xie proposed a new hybrid model namely HGN-support vector regression which is compared with six methods and the proposed method provides better accuracy [77]. Wavelet decomposition is combined with AdaBoost neural network by Shao, Deng and Cui which improves the model robustness and resolves the defects of lower accuracy. A new hybrid model called improvement in the radial basis function and in the error feedback scheme (IRBFNN-EF) is proposed by Chang, Lu, Chang and Li for short term wind speed forecasting which improves the prediction accuracy when compared with four other neural networks [78].

Liu et al proposed two hybrid methods namely ARIMA-ANN and ARIMA-Kalman filter [79]. There are non-linear forecasting hybrid algorithms such as PSO and ANFIS model [80]. The hybrid model in physical methods such as a GFS–MM5–ANN model [81] and in decomposing and filtering methods such as a Wavelet Transform (WT)–improved time series method [82]. The time series is forecasted by using a hybrid approach that uses evolutionary computation to develop a neural network that is superior than the ARIMA and ANN model [83]. Group Method of Data Handling (GMDH) based abductive networks is proposed by R.E Abdel-Aal et al and is used to forecast the mean hourly wind speed time series. This model improves the forecasting performance by automatically selecting the input variables and avoids the unnecessary errors [84]. Adaptive Neural Fuzzy Inference System (ANFIS) is the combination of neural networks and fuzzy inference system. Initially it is a neural network and then it acts as fuzzy expert system [85]. The nearest neighbor search optimized by PSO algorithm reduces the prediction error by René Jursa et al [86]. Hybridizations of global and mesoscale forecasting systems is proposed by C. Hervás-Martínez et al which uses projection hyperbolic tangent units within feed forward neural networks as final step of downscaling [87]. Tabu search achieves global optimization of back propagation neural network which is simpler than correlation analysis [88]. Empirical mode decomposition (EMD) and time-series analysis is combined by Liu Xing-Jie et al which has great improvement in forecasting precision [89]. A hybrid model EMD is combined with ANN [90]. EMD is combined with LSSVM by Xiaolan and Hui in which the wind speed series is decomposed into better behaved sub-series [91]. EMD method is combined with FFNN model by Guo et al. and the accuracy of the predictions is considerably improved [92].

3. Conclusion and Future Directions

Wind speed forecasting is an important element for wind power prediction and in turn the grid operators and wind farm owners depend upon this at load dispatch centers. As discussed about the various wind speed forecasting approaches above, NWP is good at long term predictions. The simplest time series models are the persistence models. The artificial based intelligence models are neural network and fuzzy logic models. Neural Network method is also good in most of the situations. Neural networks have strong training and learning capabilities and works well for raw input data. Fuzzy logic model works well for reasoning problems. Accurate predictions are not guaranteed by single methods. Combining the single models into hybrid models is an important issue. Hybrid models always have higher performance than single models. As wind patterns are usually different and influenced by many factors, it is very difficult to develop a global method for wind speed forecasting. Compared to other approaches, hybrid methods have many advantages. Hybrid methods which have optimization and decomposition techniques provide higher accuracy in wind speed forecasting. Neural network models and Fuzzy logic models are also combined which provides high accuracy. Hybrid methods improve accuracy and performance of the model. The performance of the hybrid models vary based upon the objective of the prediction and the characteristics of the available wind data.This paper gives an idea to the researchers who are working in the field of wind speed forecasting. As future directions, the training algorithms of artificial intelligence methods can be improved to get accurate results. In order to achieve accurate results in both short and long term prediction, different physical and statistical models can be combined. Models can be implemented practically rather than theoretically. New mathematical models can be framed. There is no free and robust system for wind speed forecasting. If it is built it will be more comfortable for energy operators. The research community can also implement the current and relevant method into the software and can work on their needs.

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