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Ensemble empirical mode decomposition based adaptive wavelet neural network method for wind speed prediction

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ABSTRACT

Wind energy is one of the emerging sustainable sources of electricity. Wind is intermittent in nature. The typical grid operation of wind energy is complex. The significance of wind energy generation and integration with the grid is increasing day by day. An accurate wind speed forecasting method will help the utility planners and operators to meet the balance of supply and demand by generating wind energy. In this paper, a statistical-based wind speed prediction is implemented without utilizing the numerical weather prediction inputs. This analytical study proposes a hybrid short-term prediction approach that can successfully preprocess the original wind speed data to enhance the forecasting accuracy. The most efficient signal decomposition algorithm, Ensemble Empirical Mode Decomposition is used for preprocessing. This ensemble empirical mode decomposition technique decomposes the original wind speed data. Each decomposed signal is regressed to forecast the future wind speed value by utilizing the Adaptive Wavelet Neural Network model. The proposed hybrid approach is subsequently investigated with respect to the wind farm of South India. The results from a real-world case study in India are reported along with comprehensive comparison. The prediction performance delivered high accuracy, less uncertainty and low computational burden in the forecasts attained. The developed hybrid model outperforms the six other benchmark models such as persistence method, back propagation neural network, radial basis function neural network, Elman neural network, Gaussian regression neural network, and wavelet neural network.

1. Introduction

Renewable sources must play a vital part in reaching the goals set by Paris agreement in December 2015. And the year 2016 was one of the best years for wind energy production field. In this year, global wind power industry installed 54.6 GW with 12.6% growth in cumulative capacity. As per the Global Wind Energy Council (GWEC) report, the new worldwide total wind installed capacity was 486.8 GW by the end of 2016 [1]. Distributed energy resources (DER) technologies are helpful in reduction in greenhouse gas emissions, reduction in damages to human health, and conservation of resources [2]. And the large-scale grid integration of renewable energy sources like wind and solar imposes challenges to the electric power utility industry in terms of technical and economical point of view [3]. In order to address these challenges, an accurate and reliable forecasting is regarded as one of the best ways. This accurate wind speed prediction is useful for bundled generation and transmission expansion planning under wind generation and demand uncertainties[4]. While considering the non-linear features of the generator such as prohibited operating zone and non-smooth functions, an accurate prediction of wind speed is essential for optimal economic load dispatch planning in power systems [5]. It is very significant to determine the proper uncertainty level of the wind forecast for operational security in the day-ahead electricity market [6]. For effective unit commitment decisions with wind energy integration is possible only by optimizing the utilization of the forecast error and reserve decision [7]. Further, spatio-temporal forecasting approaches are useful for regulation actions, and maintenance scheduling for acquiring optimal operating cost [8].

Presently, many researchers and utilities have zeal for wind speed prediction investigations. These wind speed forecasting techniques are classified into three types as follows: physical approach, statistical approach, and hybrid approach [9]. Physical approach utilizes the historical data obtained from weather stations such as power and Numerical Weather Predictions (NWP). It is suitable for long-term predictions as modeling of these are complex. Statistical approach such as autoregressive moving average (ARMA) model, variants of ARMA [10] and artificial neural network (ANN) models will employ historical time-series data for modeling and forecasting the future values. These

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approaches are most accurate for short-term forecasting. And hybrid approaches are combinations of two or more of the forecasting approaches [11].

The fast growth in artificial intelligence techniques has been promoting ANN models [12]. These ANN models have been extensively used in wind speed time-series prediction due to their capability to deal with non-linearities, predominantly including back propagation neural network (BPNN) [13]. Further, the learning ability of the neural network and fuzzy system's expert knowledge is utilized for accurate forecasting using fuzzy neural network (FNN) [14]. The neural networks require a number of neurons to tackle the various problems [15]. To overcome this problem, wavelets are incorporated into them [16]. Currently, hybrid approaches such as wavelet neural networks (WNN) that combines the wavelet transforms (WT) and artificial neural networks (ANN) have drawn a lot of attention and have been extensively employed for wind speed forecasting [17]. The principal difficulty of WNN is that of the selection of wavelet transforms [18]. The translation and dilation parameters of the wavelet basis are fixed and only weights are adjustable during the training of WNN [19]. But with proper selection of wavelet transforms one can improve the forecasting accuracy and computational complexity [20]. Many other hybrid approaches have been implemented to address these problems of WNN. In [21], a hybrid approach which combines the wavelet transform (WT), radial basis function (RBF), multi layer perceptron (MLP) neural networks and imperialist competitive algorithm (ICA) for wind power production forecasting. An RBF network has been utilized for primary prediction with different learning algorithms are used for optimizing three MLP networks. The ICA was employed to optimize the weights and biases of the three MLP networks. The main demerit of this approach is that the ICA has the problem of convergence to a local minima that affects training accuracy and speed. For another case study, optimization algorithm like improved clonal selection algorithm is utilized with wavelet neural networks for future 6-h ahead wind power forecasting [22]. The problem with this is that improved clonal selection algorithm has low accuracy and slow convergence rate. Further, a hybrid model consists of singular spectrum analysis and general regression neural network with CG-BA (SSA-CG-BA-GRNN) employed to acquire 1-h and 3-h ahead forecasting [23]. Furthermore, a hybrid approach as reported in [24] is the combination of kalman Filter (KF), artificial Neural Network (ANN) and autoregressive integrated moving average (ARIMA) model. This model can effectively handle nonlinearity and uncertainty problems. The MAPE values of Iraq and Malaysia testing forecasts are 37.17% and 11.29% respectively. In [25], the authors proposed new hybrid models by integrating the best features of Support Vector Regression (SVR) with seasonal index adjustment (SIA) and Elman recurrent neural network (ERNN) model to forecast the daily wind speed values. These hybrid models are validated by utilizing the three different wind farms data of the Xinjiang region of China. Authors in [26] considered another hybrid method that is employed to achieve high accuracy of the short-term wind power forecasting (48-h-ahead) based on the adaptive neuro-fuzzy inference system (ANFIS). And a hybrid evolutionary-adaptive (HEA) approach for short-term wind power prediction (3-h-ahead) is presented in [27], which combined the wavelet transform, mutual information and evolutionary particle swarm optimization with the adaptive neuro-fuzzy inference system. This HEA approach was successfully tested on Portuguese system and the MAPE and NRMSE values were 3.75% and 2.66% respectively. The review of various hybrid models can be referred in [28].

To enhance the prediction accuracy, improved WNN is employed in this study that is adaptive wavelet neural network (AWNN). This AWNN is a combination of adaptive learning algorithm [29] and conventional WNN. Due to this adaptive learning rate, this developed hybrid model delivers rapid convergence rate and also accuracy of forecasting performance is improved [30]. For further improving the prediction accuracy, there is a need of data preprocessing technique which is significant because it eliminates the noise from data. Wavelet transforms (WT) and empirical mode decomposition (EMD) technologies can be employed to eliminate the noisy data [31]. The hybrid model for multiresolution analysis and for the future time-series prediction is developed by employing WT and ANN [32].

EMD is another decomposition method of original wind data series other than wavelet transforms. This EMD technique decomposes the time-series into intrinsic mode functions (IMFs) and a residue. Then each IMF and residue is easy to examine by SVR to forecast the 1 h, 3 h, and 5 h ahead wind speed [33]. Not only SVR there are so many models such as ANN, ARMA etc. used for wind speed forecasting in combination with EMD. For instance, authors in [34] employed two hybrid models which combines EMD, feature selection with ANN and SVM to forecast future value of wind speed. In [35], authors developed hybrid forecasting tool which combines the EMD, feed-forward neural network (FNN). Partial autocorrelation function (PACF) is utilized for selecting the inputs for EMD-FNN model. Short-term wind speed can be forecasted using a hybrid method of EMD and recursive autoregressive integrated moving average (RARIMA) algorithm [36]. This method was applied for the real-time railway strong wind warning system. However, WT is sensitive to the choice of threshold, and The main disadvantage of EMD is the phenomenon of mode mixing problem.

Fortunately, Ensemble empirical mode decomposition (EEMD) technique can overcome the limitation of EMD. And EEMD is the most powerful and enhanced signal decomposition technique used for nonlinear or intermittent time-series analysis [37]. The wind speed forecasting tool which combines the EEMD technique, feature selection, and error correction is utilized for short-time horizon prediction in [38]. And unlike other reported methodologies the authors implemented big multi-step wind speed forecasting. But this big multi-step wind speed forecasting is more difficult and complicated due to the complexity of mapping relationships. Whereas authors in [39] used fast EEMD and multilayer perceptron (MLP) neural networks for prediction. The mind evolutionary algorithm (MEA) and Genetic algorithm (GA) are employed for optimizing the MLP neural networks. These algorithms do not improve the performance of the MLP neural networks notably due to their limitation of trapping in local minima. The hybrid prediction model was built using EEMD, back propagation NN, and genetic algorithm to forecast the 10 min ahead (very short-term) and 1 h ahead (short-term) wind speed [40]. The performance of this hybrid model is not that good because the parameters such as amplitude of noise and ensemble number are not properly chosen for decomposition. An approach used for multi-step ahead forecasts which is mainly mix of the wavelet packet decomposition (WPD), fast EEMD, and Elman neural networks [41]. The forecasting performance is satisfactory in comparison with other hybrid models. The main outcomes of all the reviewing literature and comparisons, hybrid models are superior than individual forecasting models. The main idea behind combining different individual models is to utilize the superior qualities of each individual model and to optimize the developed hybrid model. As this EEMD is able to overcome the problem of mode-mixing and decomposes the raw wind time-series data into more stationary signals with different frequencies.

In this paper, the hybrid EEMD-AWNN approach is developed, which combines the EEMD technique and AWNN model. The EEMD technique is employed to decompose the raw wind speed into a finite and often small number of intrinsic mode functions (IMFs) and one residue. Then based on the forecasting horizon the Adaptive Wavelet Neural Network (AWNN) model is built. Finally, the hybrid EEMD-AWNN model is used for forecasting the future values of wind speed and analysed results proves that the proposed EEMD-AWNN model can achieve the desired result with enhanced forecasting accuracy. The principal objectives of this paper are as follows:

1. To propose a hybrid model for short-term wind speed prediction.
2. To enhance the prediction accuracy by comprehensive comparison.
3. To reduce the uncertainty in forecasting the future wind speed time-