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Intelligent and robust prediction of short term wind power using genetic programming based ensemble of neural networks

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The inherent instability of wind power production leads to critical problems for smooth power generation from wind turbines, which then requires an accurate forecast of wind power. In this study, an effective short term wind power prediction methodology is presented, which uses an intelligent ensemble regressor that comprises Artificial Neural Networks and Genetic Programming. In contrast to existing series based combination of wind power predictors, whereby the error or variation in the leading predictor is propagated down the stream to the next predictors, the proposed intelligent ensemble predictor avoids this shortcoming by introducing Genetical Programming based semi-stochastic combination of neural networks. It is observed that the decision of the individual base regressors may vary due to the frequent and inherent fluctuations in the atmospheric conditions and thus meteorological properties. The novelty of the reported work lies in creating ensemble to generate an intelligent, collective and robust decision space and thereby avoiding large errors due to the sensitivity of the individual wind predictors. The proposed ensemble based regressor, Genetic Programming based ensemble of Artificial Neural Networks, has been implemented and tested on data taken from five different wind farms located in Europe. Obtained numerical results of the proposed model in terms of various error measures are compared with the recent artificial intelligence based strategies to demonstrate the efficacy of the proposed scheme. Average root mean squared error of the proposed model for five wind farms is 0.117575.

1. Introduction

Energy production is one of the most crucial issues faced by mankind today. Conventional power generation methods are dependent not only on the fossil fuel, but they also produce environmental pollution. The gradual rise in the ecological pollution and the exhaustion of the fossil fuel capitals has stimulated the exploration for unpolluted and clean energy resources. Wind power has emerged as a promising alternate energy source, and it is gaining popularity because of its potential to produce power on commercial scale without any adverse effects on environment. Since 1990, wind energy capacity has been doubling every three and half year [1]. Due to inherent irregular and erratic attributes of wind, the produced wind power is typically uncontrollable and affects the power distribution grid. On account of integration of wind energy into the framework, it thus is required to ensure the reliable power distribution. Consequently, wind power must be predicted in advance either on short term basis i.e. from few minutes to a day or on long term basis that varies from days to months and years. Accurate wind power forecast on short term basis ensures reliable distribution of energy to wind turbines.

The development of wind power prediction methodologies can be originated earlier to the contribution of Brown, Katz, and Murphy (1984) who used simple model based on time series for wind forecasting for the site under consideration, and then converted the resulting wind forecast to electrical power generation by using the theoretical manufacturer's power curve [2]. Since then several mature approaches for wind power forecasting and its

Abbreviations: ANN, Artificial Neural Networks; GP, Genetic Programming; GPeANN, GP based ensemble of Artificial Neural Networks; MI, mutual information; MHNN, Modified Hybrid Neural Network; EPSO, Enhanced Particle Swarm Optimization; RBFNN, Radial Basis Function Neural Network; LM, Levenberg-Marquardt; BFGS, Broyden-Fletcher-Goldfarb-Shanno; BR, Bayesian Regularization; RMSE, Root mean square error; MAE, Mean Absolute Error; SDE, Standard Deviation of Errors.

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management have been exploited recently, exclusively in countries with a major fraction of wind energy in their entire capacity. These approaches can commonly be categorized into physical models and statistical models or even combination of physical and statistical models [3]. Physical methods use physical laws governing atmospheric behavior to infer local wind speed and then the estimated local wind speed is used to estimate corresponding power. These methods consider different physical features of location, for instance, surface coarseness, turbulence, obstacles, stratification of the atmosphere, etc. to reckon wind speed and replace it into wind power by means of power curves of wind turbines [2].

Statistical methodologies figure out the relationship among set of illustrative variables and wind power by using the historical data. Statistical methods and neural networks have been widely used to predict wind speed or wind power including autoregressive moving average (ARMA) model and artificial neural networks for hourly prediction and conclude that their models perform better for one hour in advance prediction than few [4]. Carlos et al. presented three methods of Kalman filtering which generate robust outliers for wind speed prediction for next step [5]. They compared their results on the basis of performance measures of skewness and kurtosis. Zhe Song proposed a Markov-switching model and used Bayesian inference to estimate its parameters to forecast wind speed [6]. Hybrid approach based on wavelet transform and SVM has been proposed by Liu et al. [7] and Wavelet Neural Network (WNN) with multi-dimensional Morlet wavelets based activation functions of the hidden neurons has been proposed by Chitsaz [8].

Models based on artificial intelligence for instance include artificial neural networks and their hybrids. Exploiting neural networks ensemble feature selection, Mabel and Fernandez predicted wind power involving three input variables of wind speed, relative humidity and generation hours [9]. Jianwu and Wei developed wavelet support vector machines (SVM) based model by proposing a new kernel to improve generalization capability of SVM [10]. Amjady et al. proposed ridgelet neural networks (RNN) based forecast engine using ridgelet functions as activation function and utilized differential evolution algorithm to train RNN [11]. A novel approach based on neural networks with modified harmony search technique is proposed by Amjady et al. to overcome over fitting problem and getting trapped in local minima [12].

Generally, physical methods are implemented to predict wind power on long term basis, while statistical methodologies perform better in short term forecasts [13]. For wind power prediction, attempts have been reported using other statistical methods that include hybrid approach of least squares support vector machines and gravitational search algorithm [14]. Another ensemble short term prediction technique is proposed exploiting Gaussian Processes with neural networks [15]. Time series method based on Bayesian structural break model for wind speed prediction has been performed [16]. However, machine learning based hybrid approach include ANN and chaotic shark smell optimization (CSSO); where CSSO is used to optimize the number of nodes for hidden layer to increase the efficiency of training process [17]. Another hybrid approach combines modified hybrid neural network and Enhanced Particle Swarm Optimization. Their proposed forecasting engine avoids overfitting and trapping in local minima [18]. Grassi and Vecchio [13] proposed a two-hidden layer neural network, with each hidden layer comprising three neurons. The neural network has one representative output neuron indicating total produced wind energy of the farm. The algorithm used to train this network is Back Propagation. In the first hidden layer, the activation function used is hyperbolic tangent function, while in case of second hidden layer; a logarithmic sigmoid function has been taken as an activation function. Moreover, for the interested readers, reviews on the combined and hybrid strategies for wind speed and power prediction can be found in the literature [19]. Exhaustive reviews for statistical and hybrid techniques with their scope, significance and applications are discussed in [20], and reference therein.

Among implementations of hybrid techniques, Amjady et al. introduced the pioneering work in the field of short term wind power prediction [17]. They developed in [18], a wind power prediction system comprised of two-steps; initially, features are selected and then a prediction system is employed. They performed feature selection using the concept of irrelevancy and redundancy based filters exploiting mutual information (MI). Their forecast engine comprises Modified Hybrid Neural Network (MHNN), which makes use of Enhanced Particle Swarm Optimization (EPSO) for weight optimization. In their forecast engine, four different neural networks are used along with EPSO for weight adjustments. The first neural network is Radial Basis Function Neural Network (RBFNN) acting as an auxiliary predictor. This neural network has single hidden layer with 20 neurons in it. Initial forecast of this neural network along with the selected features is transferred to the next neural network which is Levenberg-Marquardt (LM) neural network. After training the neural network, the weights are adjusted using EPSO, and then the forecasted target output and the adjusted weights are transferred to the second neural network. This process also repeats for the remaining two neural networks, which are Broyden-Fletcher-Goldfarb-Shanno (BFGS) neural network and Bayesian Regularization (BR) neural network. Except auxiliary predictor all the neural networks in MHNN have single hidden layer with 3 neurons in it. The MHNN proposed by Amjady et al. [18] is an ensemble regressor that works in series of base predictions.

The novelty of the reported work lies in creating ensemble wind power predictor by intelligently developing a combined and robust decision space and thereby avoiding large errors due to the sensitivity of the series of individual wind predictors. Additionally, owing to the inherent variability of wind power production, development of a relatively stable wind predictor becomes more important. Particularly, hybrid approach of using GP with ANNs has been implemented first time for short term wind power prediction. Following are the main contributions of this work:

(a) In serial combination of wind power predictors [18,21], the error keeps accumulating stream to the next power predictors, however, the proposed intelligent ensemble wind predictor overcomes this drawback by introducing Genetic Programming (GP) based semi-stochastic combination of neural networks. GP has the built-in capability of parameter optimization as well which helps in avoiding parameter search.
(b) The learning and searching capabilities of GP are exploited to develop a nonlinear mapping of the individual decision spaces of the distinct wind predictors into another decision space that is more effective and robust compared to the individual decision spaces. This way, the proposed GP based ensemble of ANN (GPeANN) becomes capable of dealing with the potentially falter output of individual wind predictor due to the variations in the meteorological measures.
(c) The GP enables us to evolve a tree equivalent to a mathematical expression that is able to clearly and effectively model the existing relationship between features (meteorological measures) and the target variable (wind power) through the development of a nonlinear decision space.

The remaining part of the paper is arranged as such: in Section 2, the details of predicting wind power on short term basis is proposed; in Section 3, some of the existing forecasting methods are