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ASOC-4606; No. of Pages 22
ARTICLE IN PRESS

Applied Soft Computing xxx (2017) xxx–xxx

Contents lists available at ScienceDirect

Applied Soft Computing

journal homepage: www.elsevier.com/locate/asoc

Short-term wind speed and wind power prediction using hybrid empirical mode decomposition and kernel ridge regression

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A R T I C L E I N F O

Article history:
Received 28 September 2016
Received in revised form 2 December 2017
Accepted 3 December 2017
Available online xxx

Keywords:
Wind speed and power forecasting
Empirical mode decomposition
Kernel ridge regression
Random vector functional link network
Extreme learning machine
Mutated firefly algorithm
Multistep prediction

A B S T R A C T

This paper presents an efficient non-iterative hybrid empirical mode decomposition (EMD) and kernel ridge regression (KRR) for significantly accurate short-term wind speed and wind power prediction. The original non-linear and non-stationary wind speed and wind power time series data are decomposed using EMD to isolate the mutual effects between different components. The proposed EMD-KRR model is tested for predicting wind speed and wind power time series data over a time horizon spanning intervals of 10 min, 30 min, 1 h and 3 h ahead, respectively. Further the performance of EMD-KRR prediction model is compared with two other widely used non-iterative prediction models like EMD based Random vector functional link network (RVFL), and EMD based Extreme Learning Machine (ELM). Also an iterative Mutated Firefly Algorithm with Global Optima concept (MFAGO) optimized RVFL network is used for comparison to prove the advantages of non-iterative models over the iterative ones. The performance metrics of the proposed EMD-KRR and EMD-RVFL confirm the effectiveness and precision in producing an accurate forecast of both wind speed and wind power in comparison to all other prediction models using the wind power data from three real world wind farms. Further a fast reduced version of the EMD-KRR is presented in the paper to reduce the computational overhead substantially using randomly selected support vectors from the data set while resulting in a reasonably accurate forecast.

1. Introduction

Now-a-days the demand of renewable energy sources (RESs) has been increased to deal with electrical energy crisis and atmospheric issues like global warming, environment pollution etc. Wind energy is one of the rapidly growing RES which is available in plenty, clean in nature and environment friendly. Wind power generation system can be integrated to the utility grid or can directly supply power to the loads at the remote location where wind energy is rich in quantity [1]. The wind speed is one of the most complex natured weather parameter due to its dependence on different parameters like rotation of world, topographical properties of earth, temperature and pressure difference. The irregular nature of wind power, due to its high correlation with the non-stationary and non-linear wind speed, is the greatest obstruction to integrate the wind power system with the existing power system. The system operator faces different challenges like operational problems (power quality, fixed system frequency, power balance etc.), economic problems (unit commitment, economic load scheduling, spinning reserve calculations etc.), and planning problems at the time of integration of wind system to the main grid. Wind speed and wind power forecasting help the system operators to make the decisions of power generation schedules and dispatch at the conventional power plant and to find out the reserve power. Short term prediction of wind speed and wind power is vital for the planning & development of wind power system, scheduling of other non-wind generators for unit commitment and trading of electricity at certain electricity markets. Accurate prediction of wind energy production is also important for the wind farm owners as well as for the producers. The accurate prediction of wind power helps them to work efficiently in the wind electricity market by taking decisions like sale of energy and thus to increase the production & profit.

Till today different forecasting models have been deigned to predict wind speed and wind power produced by the wind farms. The forecasting models are divided into three types and they are (i) physical method [2–4], (ii) statistical method [5–11] and (iii) computational intelligence type method. The physical method depends upon several physical/meteorological attributes like temperature, pressure, obstacles, surface roughness etc. to predict the wind speed and wind power. For better prediction, these methods need lots of computation and detailed descriptions about the atmosphere. Time series models [12,13] require less information to design the model but the performances of these models are very slow. The statistical methods like auto-regressive (AR), moving

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https://doi.org/10.1016/j.asoc.2017.12.010
1568-4946/

average (MA), combination of both AR and MA i.e. autoregressive moving average (ARMA) and autoregressive integrated moving average (ARIMA) etc. are normally used for short term forecasting. But these statistical time series models are linear in nature and therefore are incapable to accurately predict the non-linear and non-stationary wind speed/wind power fluctuations. Artificial intelligence models such as artificial neural network (ANN) and its variants [14–18], fuzzy logic (FL) based systems [19–21], Support vector machine (SVM) [22,23], etc. are efficient and useful to forecast wind power or wind speed time series data. Also different hybrid methods like ARIMA-ANN [24], fuzzy inference system (ANFIS) [25], EMD based ANN technique (EMD-ANN) [26–28], EMD based SVR [29] have been developed by combining more than one method together and these methods have better performance and more prediction accuracy as compared to single methods. Most of the ANN based techniques or their hybrid variants like probabilistic neural networks or generalized regression neural network use gradient descent learning algorithm and suffer from slower convergence speed, local minima, over fitting, and generalization problems producing not very accurate forecasts. On the other hand the Support vector machine (SVM) has the limitations like scalability problem, computational complexity, slow speed and high memory requirements for large scale problems, etc.

To overcome these limitations single layer feedforward neural networks with random hidden layer weights (FNNRW) were proposed by Schmidt et al. in 1992 [30] and Braake et al. in 1995 [31], where the training procedure comprises random feature mapping in the first step and then solving the network output parameters using a non-iterative pseudo inverse least squares solution. A variant of FNNRW is the widely used Random Vector Functional Link (RVFL) network [32,33] proposed by Pao et al. in 1994 and also presented by Igelnik et al. in 1995, that shares the same parameter training steps as the FNNRW. However, the RVFL network has direct connections between input layer and the output layer. Subsequently the training steps of RVFL network has improved substantially along with new applications as presented in references [34–38]. Also it is well known that the performance of RVFL network deteriorates without the use of direct links between the input and output layers [35–37]. In recent years another non-iterative variant of either FNNRW or RVFL known as ELM [39,41] was presented by Huang et al. in 2004 and 2006 for handling regression and classification problems. Further ELM is also a FNNRW without the bias term, and when compared to RVFL network ELM has no direct link between the input and output layers. Recent research [34,35] showed direct links in RVFL improved the performance while bias term did not have any impact. A pseudo inverse least squares formulation was proposed to train the weights between the hidden layer neurons and the output neuron for the RVFL with direct links or randomized neural network FNNRW or the ELM to obtain solution in a closed form. Thus in this paper both RVFL and ELM have been considered for both wind speed and wind power forecasting due to their simple architecture, fast learning speed and, generalization performance. However, the learning performance of these networks is highly influenced by the choice of the number of hidden layer neurons and their activation functions, which are still an unsolved problem. Also with a chosen number of hidden layer neurons, ELM produces a large variation in the prediction accuracy for different trial runs, and therefore kernel functions based forecasting tools are used to overcome these limitations.

Among the various kernel based regression methods, Least Squares Support Vector Machine (LS-SVM) presented by Suykens et al. [42] in 1999 and kernel ridge regression (KRR) presented by Saunders et al. [43] in 1998 are found to have wide applications in forecasting. KRR is a nonlinear regression approach where a nonlinear kernel function is applied in the original space for defining an inner product in a transformed space of higher dimension to provide generalization performance based on regularization least square. The high dimensional feature space is determined by a kernel function that describes the similarity between the pair wise input and output data samples satisfying Mercer's condition. Further KRR is particularly attractive than the LS-SVM for its simple implementation, fast processing speed and accuracy. Also ELM can be used with kernels (KELM) which is presented by Huang et al. in the year 2012 and non-kernels with feature mapping function [41]. The mathematical expressions for both the KRR and KELM are the same. But as KRR was presented much earlier to KELM, and therefore in this paper KRR [44–48] is considered for both wind speed and wind power forecasting.

Further handling nonlinear and non-stationary data like the wind power or wind speed time series, it is useful to decompose the time series into intrinsic mode functions using EMD and a residue and make them as inputs to RVFL, ELM, and KRR models. It is well known from the literature that each IMF of the decomposed time series is easier to analyze by using ARMA, ANN, and Support vector regression, etc. Besides using EMD does not require more than one predictor to model the decomposed time series and there is no restriction for including more than one-step time lagged predictors. Since both wind speed and wind power time series are nonlinear and non-stationary in nature this paper proposes unified hybrid models, which are quite efficient and fast to forecast both these time series as compared to other earlier iterative approaches.

Thus the final objective of this paper is to propose an efficient hybrid non-iterative approach like the EMD-KRR and its kernel variants and compare its performance with other non-iterative EMD-RVFL, EMD-ELM models for the efficient short-term wind speed and wind power prediction. Here EMD gives a deep insight to the original data which improves the robustness of the proposed KRR method using a variety of kernel functions. Further to reduce the computational burden of the KRR forecasting model that deals with a large data matrix, a faster reduced version [49,50] known as reduced wavelet KRR (RWKRR) is also presented in this paper using a number of random support vectors from the data resulting in a reasonable accuracy. Besides various non-iterative approaches mentioned above, an alternative iterative hybrid EMD-RVFL network and random weights optimization through a Mutated Firefly Algorithm [51,52] combined with Global Optima concept (MFAGO) is proposed in this paper for a critical comparison. This alternative iterative technique will be known as MFAGO-EMD-RVFL network which will be used to validate the robust prediction accuracy and faster convergence to the true values of the non-iterative EMD-KRR model. Two other swarm optimization techniques like the ALO (Ant Lion Optimizer) [53] and Moth-flame optimization (MFO) [54] algorithms are also considered in this paper for comparison of convergence characteristics and forecasting performance with respect to the iterative MFAGO-EMD-ELM technique.

The major contributions of the paper are listed as follows:

1. An unified non-iterative approach using EMD-ELM, EMD-RVFL, EMD-KRR models is presented for both short-term wind speed and wind power predictions.
2. Initially, EMD technique is proposed to decompose the historical wind data into various intrinsic mode functions (IMF's), in order to extract a more clear and distinctive information. These IMFs are then used as inputs to the various non-iterative and iterative models in order to predict the 10 min, 30 min, 1 h, 3 h, and multi-step ahead wind speed and wind power variations
3. Further, the performance of the proposed prediction models is compared with the widely used wavelet kernel based LS-SVM technique for various short-time intervals, i.e., 10 min, 30 min, 1 h and 3 h ahead wind speed and wind power predictions, respectively. Using different performance metrics it has been shown that the non-iterative EMD-WKRR (wavelet kernel based