Electrical Power and Energy Systems 78 (2016) 910–915

Contents lists available at ScienceDirect

Electrical Power and Energy Systems

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

A hybrid model of EMD and multiple-kernel RVR algorithm for wind speed prediction

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ARTICLE INFO

Article history:
Received 13 April 2015
Received in revised form 6 November 2015
Accepted 17 November 2015
Available online 28 January 2016

Keywords:
Wind speed
EMD
Multiple-kernel RVR model
Prediction method

ABSTRACT

In this paper, the hybrid model of empirical mode decomposition and multiple-kernel relevance vector regression algorithm (EMD-MkRVR) is presented for wind speed prediction. The multiple-kernel relevance vector regression (MkRVR) model includes radial basis function (RBF) kernel and polynomial kernel whose proportions are determined by a controlled parameter. Grid method is used to select the kernel parameters and controlled parameter in this study. In addition, wind speed can be regarded as a signal and decomposed into several intrinsic mode functions (IMFs) with different frequency range by empirical mode decomposition (EMD), the prediction models of these decomposed signals can be established by MkRVR with their respective appropriate embedding dimension. The experimental results show that the EMD-MkRVR model has a better prediction ability for wind speed than the RBF kernel RVR (RBFRVR) model and the polynomial kernel RVR (PolyRVR) model.

Introduction

Wind energy is a sustainable source for generating electricity, and is regarded as one of the most important green energies [1–3]. The forecasting effect of wind energy is directly dependent on the prediction accuracy of wind speed because of the important impact of wind speed on wind power generation [4,5]. Recently, some intelligent prediction methods have been presented for wind speed prediction, such as support vector regression algorithm [6]. Support vector regression (SVR) algorithm has the better generalization performance than artificial neural networks, particularly under the condition of small training samples [7]. Relevance vector regression (RVR) algorithm is an intelligent learning technique based on sparse Bayesian framework [8], as the number of relevance vectors in RVR is much smaller than that of support vectors in SVR, which makes RVR have a sparser representation compared with SVR. In addition, there is no need to set the penalty parameter in RVR, which makes RVR more convenient to use than SVR. Thus, RVR has a better application prospect in wind speed prediction.

In this study, the hybrid model of empirical mode decomposition and multiple-kernel relevance vector regression algorithm (EMD-MkRVR) is presented for wind speed prediction. The multiple-kernel relevance vector regression (MkRVR) model includes radial basis function (RBF) kernel and polynomial kernel whose proportions are determined by a controlled parameter. As the selection of the parameters of the kernel functions and the controlled parameter has a certain influence on the prediction results of the MkRVR model, grid method is used to select its kernel parameters and controlled parameter. In addition, wind speed can be regarded as a signal and decomposed into several IMFs with different frequency range by empirical mode decomposition (EMD), the prediction models of these decomposed signals can be established by MkRVR with their respective appropriate embedding dimension. Thus, the corresponding MkRVR models of these decomposed signals have appropriate embedding dimensions, kernel parameters and controlled parameters. In order to show the superiority of the proposed EMD-MkRVR method, the RBF kernel RVR (RBFRVR) models with several different embedding dimensions and RBF kernel parameters, and the polynomial kernel RVR (PolyRVR) models with several different embedding dimensions and polynomial kernel parameters are used to compare with the proposed EMD-MkRVR method. The experimental results show that the EMD-MkRVR model has a better prediction ability for wind speed than the RBFRVR model and the PolyRVR model.

Multiple-kernel relevance vector regression model

Let $T = \{\mathbf{x}_l, t_l\}_{l=1}^{N}$ be a set of the training data, where $\mathbf{x}_l$ denotes the input vector and t_l denotes the corresponding output target, the target t_l includes the additive noise, that is,

$$t_l = y(\mathbf{x}_l, \mathbf{w}) + \varepsilon_l \tag{1}$$

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http://dx.doi.org/10.1016/j.ijepes.2015.11.116

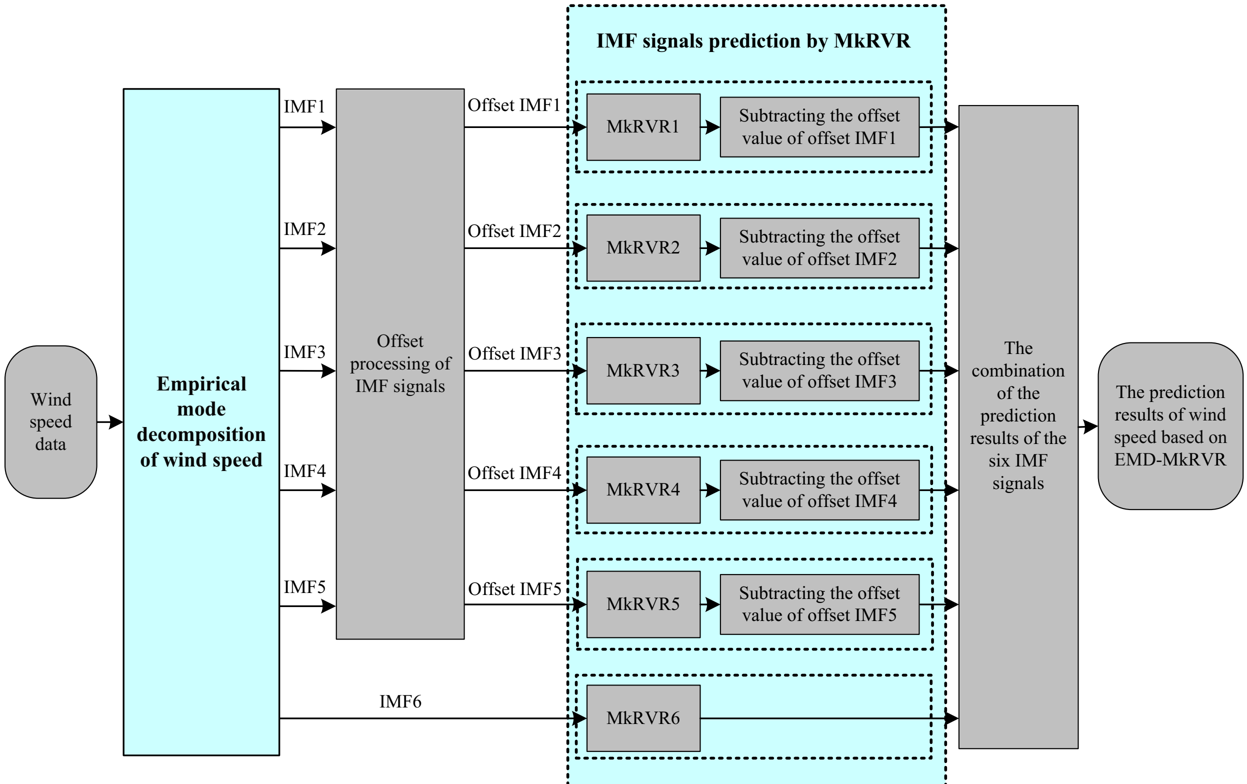

Fig. 1. Wind speed prediction process based on EMD and multiple-kernel RVR model.

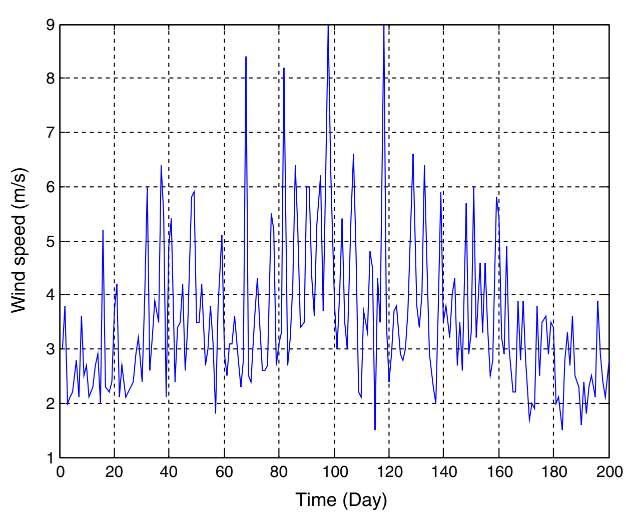

Fig. 2. Wind speed data of the first 200 days of Hohehot in 2013.

where ε_l is assumed to be mean-zero Gaussian noise with variance σ^2.

The relevance vector regression model [9] which consists of a linear combination of the weighted kernel functions can be described as follows:

$$y(\mathbf{x}, \mathbf{w}) = \sum_{i=1}^{N} w_i K(\mathbf{x}, \mathbf{x}_i) + w_0 \tag{2}$$

where $K(\mathbf{x}, \mathbf{x}_i)$ is the kernel function, $\mathbf{w} = [w_1, w_2, \ldots, w_N]$ is the weight vector, and w_0 is the bias.

In order to improve the generalization ability of RVR, a multiple-kernel relevance vector regression model is constructed by the local kernel function and global kernel function. The RBF kernel (K_{RBF}) is a typical local kernel, in this study, the Gaussian kernel is used as the RBF kernel, which can be defined as follows:

$$K_{RBF}(\mathbf{x}_i, \mathbf{x}_j) = \exp\left(-\frac{\|\mathbf{x}_i - \mathbf{x}_j\|^2}{\gamma^2}\right) \tag{3}$$

where γ denotes the kernel parameter of the RBF kernel.

And the polynomial kernel (K_{Poly}) is a typical global kernel, which can be defined as follows:

$$K_{Poly}(\mathbf{x}_i, \mathbf{x}_j) = \left(\mathbf{x}_i \cdot \mathbf{x}_j^T + 1\right)^d \tag{4}$$

where d denotes the kernel parameter of the polynomial kernel.

The proportions of K_{RBF} and K_{Poly} are determined by the controlled parameter u. Thus, the multiple-kernel function can be expressed as follows:

$$K_{mix(RBF,Poly)}(\mathbf{x}_i, \mathbf{x}_j) = uK_{RBF}(\mathbf{x}_i, \mathbf{x}_j) + (1-u)K_{Poly}(\mathbf{x}_i, \mathbf{x}_j) \tag{5}$$

where $u(0 \leqslant u \leqslant 1)$ denotes the controlled parameter.

Grid method is used to select the kernel parameters γ, d and controlled parameter u of the MkRVR model. Mean validation error of all training samples can be used to evaluate the performance of the MkRVR models with the different values of the kernel parameters γ, d and controlled parameter u. Mean validation error can be defined as follows:

$$\tilde{e} = \frac{1}{H}\sum_{q=1}^{H}\left|\frac{y_q - \hat{y}_q}{y_q}\right| \tag{6}$$

where y_q is the actual value, $\hat{y}_q$ is the validation value, and H is the number of the training samples.