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A hybrid technique for short-term wind speed prediction

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ABSTRACT

This study proposes a hybrid forecasting approach that consists of the EWT (Empirical Wavelet Transform), CSA (Coupled Simulated Annealing) and LSSVM (Least Square Support Vector Machine) for enhancing the accuracy of short-term wind speed forecasting. The EWT is employed to extract true information from a short-term wind speed series, and the LSSVM, which optimizes the parameters using a CSA algorithm, is used as the predictor to provide the final forecast. Moreover, this study uses a rolling operation method in the prediction processes, including one-step and multi-step predictions, which can adaptively tune the parameters of the LSSVM to respond quickly to wind speed changes. The proposed hybrid model is demonstrated to forecast a mean half-hour wind speed series obtained from a windmill farm located in northwestern China. The simulation results suggest that the developed forecasting method yields better predictions compared with those of other popular models, which indicates that the hybrid method exhibits stronger forecasting ability.

1. Introduction

Wind energy has become one of the most popular and fastest-growing renewable energy resources around the world. Over the past five years, wind energy has experienced rapid growth at an average rate of 31%. As of June 2013, the installed wind power capacity has amounted to 296,255 MW globally, and the installed wind turbine generators globally can generate approximately 3.5% of the global electricity demand [1]. However, the penetration of large amounts of the newly increased wind power capacity poses many challenges to electricity energy system operations, including the management of the variability of wind power generation, market integration, interconnection standards, power quality and power system stability and reliability [1,2].

Wind power generation is closely related to a significant factor-wind speed (the nonlinear relationship (i.e., basically cubic) between wind power and wind speed). Wind speed forecasting can be implemented according to the time scales of wind speed data and the purpose of the forecast. Short-term prediction, as one important type of wind speed forecasting, is instrumental in the planning of economic load dispatch and load increment/decrement decisions made with respect to the management of a significant amount of wind power. To forecast short-term wind speed, various methods and approaches have been proposed in the literature, such as persistence methods, physical modeling methods, time series models and soft computing approaches, over the past decades. The persistence method, which is generally employed as a benchmark for comparison with other tools [3], utilizes recent wind speed data for forecasting. The physical models make use of various weather data to forecast wind speed. The Numerical Weather Prediction [4–6] model represents a typical physical approach to producing wind forecasts for large-scale areas.

Time series models are widely used tools in the field of forecasting and have also been proposed for short-term wind speed forecasting. The models are established using historical data to tune the model parameters and by examining whether the fitting residuals possess the characteristics of a random walk process. Typical examples of time series models include the ARMA (autoregressive moving average) [7], the ARIMA (autoregressive integrated moving average) [8], the FARIMA (fractional autoregressive integrated moving average) [9], exponential smoothing techniques [10] and grey predictors [11].

Soft computing methods are extensively utilized by scholars to forecast wind speed because such methods provide suitable performance capabilities, especially in tackling nonlinear problems. ANNs (Artificial neural networks) are the most popular approaches

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Nomenclature

Λ_n	the nth segment in [0,π]
ω_n	the nth detected maxima of Fourier spectrum
∀	randomly assign
$\hat{\phi}_n(w)$	the empirical scaling function
$\hat{\varphi}_n(w)$	the empirical wavelets
λ	the real number belong to the interval [0,1]
⟨⟩	inner product
$f(t)$	the signal
$\overline{\varphi_n(\tau - t)}$	the conjugate of the empirical wavelets
$w_f^\varepsilon(n,t)$	The detail coefficients
$P(x\rightarrow y)$	the probability of transitioning from the current state x to y
T_k	the generation temperature
T_k^{ac}	the acceptance temperature
$E(x)$	the energy of the current state
$G(x\rightarrow y)$	the generation probability
$A(x\rightarrow y)$	the acceptance probability
$U(T_k,k)$	the generation temperature schedules
$V(T_k^{ac},k)$	the acceptance temperature schedules
W	the weight vector
b	the bias term
$\Phi(x)$	the nonlinear mapping function
e_i	the error variable
α_i	the Lagrange multiplier
EWT	empirical wavelet transform
CSA	coupled simulated annealing
PACF	partial autocorrelation function
BPNN	back-propagation neural network
RBFNN	radial basis function neural network
ANNs	artificial neural networks
WT	wavelet transform (WT),
GA	genetic algorithm (GA)
EMD	empirical mode decomposition
SVM	support vector machine
LSSVM	least square support vector machine
PSO	particle swarm optimization algorithm,

Definition

Multistep ahead forecast suppose that we are at the time index h and are interested in forecasting $\hat{r}_{h+l}$, where $l \geq 1$. The time index h is called the forecast origin and the positive integer l is the forecast horizon. Let $\hat{r}_h(l)$ be the forecast of r_{h+l}, we refer to $\hat{r}_h(l)$ as the l-step ahead forecast of r_t at the forecast origin h when $l = 1$, we refer to $\hat{r}_h(1)$ as the **one-step ahead forecast** of r_t at the forecast origin h.

among soft computing methods, which are based upon empirical risk minimization and asymptotic theories. Typical examples of artificial neural networks include the BPNN (Back-Propagation Neural Network) [12,13], the recurrent neural networks [14], the RBFNN (Radial Basis Function Neural Network) [15], the Elman neural network [16], the GRNN (General Regression Neural Network) [17], the ANFIS (Adaptive Neuro Fuzzy Inference System) [18,19] and MLP (Multi-Layer Perceptron network) [20,21]. SVM (Support Vector Machine) [22–27] is another type of soft computing methods, which is based on a statistical learning theory and the structural risk minimization principle.

In recent years, hybrid approaches to wind speed forecasting have become increasingly popular. A hybrid model consisting of a WT (Wavelet Transform), GA (Genetic Algorithm) and SVM was put forward to enhance the accuracy of short-term wind speed forecasting [22]. In the literature [23], a hybrid model was proposed to forecast wind speed for a Spanish wind farm, in which two different evolutionary computation techniques (an EP (Evolutionary Programming) algorithm and a PSO (Particle Swarm Optimization) algorithm) were used to tackle the hyper-parameters estimation problem in SVM. Guo et al. [28] reported a hybrid model which integrated EMD (empirical mode decomposition) with feed-forward neural network for the wind speed forecasting. Haque et al. [29] presented several hybrid approaches that combined a similar days method with soft computing models (a BPNN, a RBFNN, and an adaptive neuro-fuzzy inference system) for short-term wind speed prediction. Li et al. [30] proposed a combinational approach which combined three types of artificial neural network models that were independently used for prediction through weights determined by a Bayesian combination algorithm. Blonbou [31] suggested an adaptive short-term wind power prediction scheme using neural network predictors along with adaptive Bayesian learning and Gaussian process approximation. Recently, Bhaskar and Singh [32] proposed a hybrid forecasting approach involving a WT technique and an adaptive wavelet neural network for wind speed prediction, in which the wavelet technique is employed to decompose wind series, and the adaptive wavelet neural network predicts wind speed for each decomposed subseries. Nima Amjady et al. [33] attempted to apply a hybrid strategy consisting of a feature selection component and a forecasting engine for wind power forecasting. The feature selection component utilized two filters to eliminate irrelevant features and redundancy from the set of candidate inputs, and the forecasting engine, a hybrid neural network optimized by a new, enhanced particle swarm optimization algorithm, provided wind power predictions.

This study utilizes the concept of hybrid prediction and proposes a hybrid forecasting approach for more accurately estimating short-range wind speed. The developed hybrid method is examined by one-step ahead and multi-step ahead forecasting of the mean 30-min wind speed of the observation site located in northwestern China. The simulation results reveal that the hybrid forecasting method outperforms other popular algorithms.

The remainder of this paper is organized as follows. Section 2 discusses the drawbacks of existing models and the contributions of the proposed model, and section 3 introduces the required individual models and describes the developed hybrid model. In section 4, the wind speed predictions and advantages of the developed strategy are analyzed and discussed through comparisons with other benchmark models. Finally, the conclusions of the study are presented in section 5.

2. Contribution

Time series models mentioned in section 1 are established on the linear assumption. They can cope with the wind speed forecasting problem when the wind speed series presents the linearity characteristic [34]. However, in most situations, wind series does not always change in a linear manner, thus affecting the accuracy of predictions. Therefore, soft computing methods are proposed by scholars to tackle the problems. ANNs have advantages over