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A novel hybrid approach for wind speed prediction

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ABSTRACT

It is important to improve the accuracy of wind speed predictions for wind park management and for conversion of wind power to electricity. However, due to the chaotic and intrinsic complexity of weather parameters, the prediction of wind speed data using different patterns is difficult. A hybrid model known as SAM–ESM–RBFN is proposed for capturing these different patterns and obtaining better prediction performance. This model is based on the seasonal adjustment method (SAM), exponential smoothing method (ESM), and radial basis function neural network (RBFN). The mean hourly wind speed data from two meteorological stations in the Hexi Corridor of China were used as examples to evaluate the performance of the proposed approach. To avoid randomness due to the RBFN model or the RBFN component of the hybrid model, all of the simulations were repeated 30 times prior to averaging. The SAM–ESM–RBFN model numerically outperformed the following models: the Holt–Winters model (HWM), the multilayer perceptron neural network (MLP), the ESM, the RBFN, the hybrid SAM and ESM (SAM–ESM), the hybrid SAM and RBFN (SAM–RBFN), and the hybrid ESM and RBFN (ESM–RBFN). Overall, the proposed approach was effective in improving the prediction accuracy.

1. Introduction

Special attention has been focused on renewable energy due to environmental deterioration and conventional resource depletion. Wind power is a clean and non-polluting renewable energy source. Recently, the amount of energy generated by wind power has rapidly increased. The installed wind power capacity increased by nearly 200% between 2005 and 2009 [62]. In 2009, 340 TW h of wind energy was generated worldwide, which accounted for 2% of electricity usage worldwide. In addition, the capacity of wind-powered generators reached 159.2 GW in 2009. The amount of energy produced from wind sources has doubled over the last 3 years and is expected to increase in the future [14].

However, many problems have occurred with the rapid development of wind power. One of the main problems associated with generation of wind power is the continuous fluctuation of wind speed. Fluctuating wind speeds make it difficult to predict how much power will be injected into a distribution network, which can result in energy transportation issues [47]. Thus, improving the accuracy of wind power prediction is highly important. It is widely accepted that wind power prediction should be based on actual wind signal forecasts rather than on the output power of wind turbines [19]. Thus, obtaining accurate wind speed predictions has become increasingly important.

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Generally, wind speed predictions can be classified into two categories: short-term predictions (time scales of minutes, hours, and days) and long-term predictions (time scales of months and years). For short-term predictions, accurate predictions are important in minimizing scheduling errors, which impact grid reliability and market-based ancillary service costs [27]. For long-term predictions, prediction accuracy is important for site selection, performance prediction, windmill planning, and selection of the optimal wind machine size for a particular site [36]. The focus of this study was on short-term wind speed prediction.

Many prediction methods have been developed over the last two decades. These methods can be divided into two categories: statistical models and machine-learning models. Statistical models primarily use a time series approach and have been successfully applied for forecasting [14,27,44,49]. These models are based on the assumption that a linear correlation structure exists among time series values. Therefore, non-linear patterns cannot be captured using these models. To overcome this limitation, machine-learning models (which primarily include artificial neural networks (ANN), support vector machines, and fuzzy logic methods), have been used to improve non-linear time series predictions [9,12,17,21,22,26,30,31,34,38,50,53,55,57].

Wind is a weather-driven renewable resource that depends on climate. The two most commonly encountered phenomena in wind speed series are seasonal variations and trend variations [27]. However, seasonal variations are often neglected in wind speed series predictions, and the large seasonal variations result in large prediction deviations. According to Zhang and Qi [60], de-seasonalization can dramatically reduce the prediction errors in seasonal time series. The seasonal adjustment method (SAM) was used to decompose the time series into seasonal and trend components as well as to simulate and predict the seasonal component. Thus, the SAM was used to pre-process raw wind speed data in this study. Beyond the seasonal component of the wind speed series, the trend component is complex and contains linear and non-linear characteristics. Thus, the sole use of a statistical model or a machine-learning model cannot adequately forecast the wind speed if a time series contains linear and non-linear patterns, and accordingly, no single method or model can work well in all situations [8,61]. Generally, it is more effective to combine different models that use different sources of information [25,41,52]. Hybrid models have been rapidly developed to improve prediction accuracy [1,4,10,11,15,16,37,48,56]. For example, Monfared et al. proposed a new strategy for wind speed prediction that was based on fuzzy logic and artificial neural networks [37]. In addition, Fan and Liu combined a gray-related and weighted combination with the revised parameter method to predict wind speed [15]. Ata and Kocyigit applied an adaptive neuro-fuzzy inference system (ANFIS) model to predict the tip speed ratio (TSR) and the power factor of a wind turbine [1]. Furthermore, Sancho et al. discussed the application of the complete evolutionary support vector machines algorithm to real wind speed prediction problems for Spanish wind farm turbines [48].

As one of the most popular statistical models, the main advantage of exponential smoothing methods (ESM) is their robustness, which allows for fast and efficient implementation with descriptive and inferential statistics [18]. The ESM has been studied extensively for linear identification and time series prediction. However, the ESM is rarely used for wind speed prediction [33]. Artificial neural networks are useful for predicting wind speeds because they are able to capture subtle functional relationships from empirical data if the underlying relationships are unknown or are difficult to describe. Radial basis function neural networks (RBFN) are special neural networks that have been studied extensively by researchers for non-linear identification and time series prediction. A RBFN can rapidly learn complex patterns and tendencies that occur in data. In addition, RBFN can arbitrarily approximate any multivariate continuous function in a compact domain if a sufficient number of radial basis function units are provided [42,45]. Thus, ESM and RBFN were used to predict wind speeds in this study.

Due to the chaotic and intrinsic complexity of weather parameters, it is difficult to predict wind speed data or wind patterns. In this study, a hybrid model (referred to as SAM–ESM–RBFN) for wind speed prediction based on the SAM, ESM, and RBFN was proposed to capture different patterns and improve prediction performance. First, the SAM was used to eliminate the seasonal components from raw wind speed data and to predict the seasonal component. Next, the ESM and RBFN were used to capture the linear and non-linear patterns, which were used to predict the wind speed trends. Third, the predicted trend was adjusted by combining the seasonal index with the predicted trend function. Finally, the mean hourly wind speed data from the two meteorological stations in the Hexi Corridor of China were used as illustrative examples to evaluate the performance of the SAM–ESM–RBFN model. In addition, the HWM is a popular double exponential smoothing method that includes seasonal and trend components. The multilayer perceptron neural network (MLP) has often been used to predict time series. To evaluate the performance of the proposed approach, the SAM–ESM–RBFN model was compared with the HWM, MLP, ESM, RBFN, SAM and ESM (SAM–ESM) models, the hybrid SAM and RBFN (SAM–RBFN) model, and the hybrid ESM and RBFN (ESM–RBFN) model. The numerical results indicate that the proposed method outperforms these models. Thus, the proposed method is effective in improving the accuracy of wind speed predictions. The remainder of this study is organized as follows. Section 2 presents the SAM–ESM–RBFN approach for short-term wind speed prediction. Section 3 discusses the different error criteria used to evaluate the prediction accuracy. Section 4 presents the numerical results obtained from two real datasets, and the conclusions are presented in Section 5.

2. Proposed approach

This section presents the SAM–ESM–RBFN method. First, the SAM, ESM, and RBFN are briefly introduced, and the approach of the SAM–ESM–RBFN model is presented.