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Combined forecasting models for wind energy forecasting: A case study in China

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ABSTRACT

As the energy crisis becomes a greater concern, wind energy, as one of the most promising renewable energy resources, becomes more widely used. Thus, wind energy forecasting plays an important role in wind energy utilization, especially wind speed forecasting, which is a vital component of wind energy management. In view of its importance, numerous wind speed forecasts have been proposed, each with advantages and disadvantages. Searching for more effective wind speed forecasts in wind energy management is a challenging task. As proposed, combined models have desirable forecasting abilities for wind speed. This paper reviewed the combined models for wind speed predictions and classified the combined wind speed forecasting approaches. To further study the combined models, two combination models, the no negative constraint theory (NNCT) combination model and the artificial intelligence algorithm combination model, are proposed. The hourly average wind speed data of three wind turbines in the Chengde region of China are used to illustrate the effectiveness of the proposed combination models, and the results show that the proposed combination models can always provide desirable forecasting results compared to the existing traditional combination models.

Contents

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1. Introduction

Energy is critically important to the social and economic development of any nation. With the increasing industrial and economic activity over the last several decades, energy demands have grown rapidly [1]. According to the *IEA World Energy Outlook 2010*, the energy demands of China and India will account for half of the growth in global energy demands by 2050. At that point, China's energy consumption will be nearly 70% greater than that of the United States, the second greatest energy-consuming country, thus placing China as the leading energy-consuming country in the world. However, China's per capita energy consumption will still be less than half that of the United States [2]. With increasing demands for energy, traditional resources such as oil and coal remain the dominant sources of energy worldwide. However, the use of traditional resources results in the release of significant amounts of carbon dioxide, which causes serious environmental problems, especially with respect to climate change. Climate change has been recognized as an international security threat, and as such, it no longer relates only to quality of life and the environment, but it also directly affects human and global security [3]. Energy crises and climate change make renewable energy necessary. Hydroelectric, wind, biomass, solar, terrestrial heat, clean coal and nuclear energies are rapidly being developed. As a clean energy source and because of its low cost of production, wind energy is often viewed as an attractive energy option. Accordingly, wind energy has achieved maturity in the energy market and, compared to the aforementioned alternatives, has experienced the greatest growth worldwide in the past several decades. Being both convenient and environmentally friendly, wind energy meets the growing demand for electricity. Furthermore, with the cost of electricity from non-renewable sources continuing to increase, wind energy is becoming increasingly competitive [4].

Introduced 20 years ago, China became one of the world's first countries to use wind energy to generate electricity, and its development since then has been rapid. In June 2012, China's grid-connected wind power reached 52.58 million kilowatts (KW), surpassing that of the United States, the country that previously ranked first in the world in wind energy capacity with a cumulative installed capacity of 44,733.29 MW (MW). In China's national power grid, dispatch reached 50.26 million kilowatts (kW), making it the largest global wind power grid and the fastest growing power grid [5]. Reaching 60.83 million kilowatts in 2012, China's total wind power grid has been ranked first in the world for two consecutive years. Wind power accounts for 2% of the country's total generating capacity with an annual generating capacity of over 100 billion kilowatts (kW). Thus, wind power has become the third largest source of power and plays a prominent role in optimizing the energy structure and promoting energy conservation in China [6]. Given that wind power generation depends on wind speed, the main problem with wind power is that the wind speed is subject to significant fluctuations that are harmful to the wind turbines. Because the fluctuating wind speeds must then be processed and used to generate power, obtaining accurate wind speeds is important. However, because wind is air motion whose driving force is due to the uneven heating and cooling of the earth's surface and the occurrence of wind is highly uncertain in time and space because it depends on many weather factors such as pressure and temperature, obtaining accurate forecasting results for wind speed can be challenging [7].

Accordingly, many significant studies have been devoted to developing efficient forecasts for wind speed that can be divided into two categories. The first is the physical method that uses numerous physical considerations for the best forecasting accuracy. The second is the statistical method that aims at finding the relationship between the online measured power data, including traditional statistical models (such as ARIMA models, ARCH models, Kalman Fitters (KF) etc.) and machine learning (ML) models. Artificial neural networks (ANNs), as a class of methods in ML models, have been widely used in a broad range of applications [8]. Moreover, ANNs are improved and combined with other methods for improved prediction accuracy. The ANN with a statistical weighted pre-processing method (SWP–ANN) can be used to predict ground source heat pump (GCHP) systems with the minimum data set, and the simulation results show that SWP–ANN performs better than ANN [9]. Fuzzy models can be combined with ANNs to create ANFIS, which demonstrate reliable forecasting applicability [10]. However, ANNs do not always perform well, and at times the proposed wavelet neural network (WNN) does better than ANN [11]. ANNs are also widely used in wind speed prediction where their performance depends on the training data sets [12]. Support vector machine (SVM), another ML method, has had rapid development in recent years, and its performance proved to be desirable. For example, SVM has been shown to have excellent performance compared to an ANN model and an ANFIS model [13]. The least-squares support vector machine (LS-SVM) method can be used to make a modeling study of the solar air heater (SAH) system and for estimating the efficiency of SAHs with reasonable accuracy [14]. Moreover, some hybrid wind speed forecasts have also been put forward [7,9]. Though the statistical method is more seasonal to forecast wind speed compared to the physical method, it does not always capture the relationship between different data and obtain accurate forecasting results. Therefore, some hybrid wind speed forecasts are proposed; when compared with individual forecasts, the hybrid forecasts have demonstrated outstanding forecasting results. However, hybrid forecasts are based on only two or three individual forecasts. When more individual forecasts are included, using hybrid forecasts becomes difficult. Therefore, to make full use of the advantages of individual forecasts while not increasing the simulation difficulties, combination forecasts have been proposed.