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Weighted Evaluation of Wind Power Forecasting Models Using Evolutionary Optimization Algorithms

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Abstract

The unpredictability of renewable sources of energy especially wind power causes large fluctuations in the power output. The fluctuations are smoothened by building large amounts of battery storage and/or power reserve capacity. By improving the forecasting accuracy, these reserves can be reduced. We revisit the problem of short-term wind power prediction using statistical and machine learning based modeling techniques. In prior work, we developed a fusion evaluation index to rank various forecasting models. We used eight forecasting models selected from literature and seven evaluation indexes in that study. Each evaluation index was weighted in two parts – an objective normalized weight based on maximizing deviations and a subjective (expert) weight. In this paper, we use two evolutionary optimization algorithms to optimize the objective weights of the indexes. Particle Swarm Optimization (PSO) and Differential Evolution (DE) are used to produce an optimal weight strategy for the six of the seven indexes using a training data set. The weighted objective indexes are then applied to a test dataset with promising initial results. The simulation is based on seven months of actual data from a wind farm in Shanxi province, with a sampling interval of 5 minutes.

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Keywords: wind power; modeling; prediction; particle swarm optimization; differential evolution

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1. Introduction

Wind energy is characterized by intermittence and randomness, which causes the output power of wind turbines to fluctuate which adversely affects the scheduling and the stability of the power grid. Transmission system operators have to balance the electricity production so that it matches the consumption at any given time which necessitates the use of reserve power in order to compensate for these fluctuations. This reserve power lowers the environmental impact gained by using wind energy. Therefore, it is necessary to predict wind power accurately, which can reduce the need for reserve capacity and conventional power, as well as provide the basis for reasonable scheduling plan of the power supply system [1, 2].

There are two main approaches used for wind power prediction – one employs physical models of wind farms to determine the relationship between weather data from a numerical weather prediction model and the power output of the wind farm [3, 4]. The other approach uses mathematical modeling techniques such as statistical or artificial intelligence methods to model the relationship between weather prediction data and power output from historical datasets. These techniques involve using support vector machines (SVM) for wind speed prediction [5], and artificial neural networks (ANN) and neuro-fuzzy approaches for short-term wind power prediction [6-8]. Conventional statistical approaches are mostly geared towards very short-term and short-term prediction. These models are easy to formulate and are capable of providing timely forecasts. These are often based on autoregressive models (AR), moving average (MA), autoregressive moving average (ARMA) and the autoregressive integrated moving average (ARIMA). A recent survey compared ARIMA, ANN and SVM for short-term prediction of wind speed [9]. Results showed that performance of a combination of ARIMA-ANN and a combination of ARIMA-SVM performed better than ARIMA, ANN, and SVM single models

In general, the data used by the individual wind power forecasting models are not comprehensive enough, which results in relatively large errors at some forecasting points. To mitigate this and to improve the forecasting accuracy of wind power, the idea of fusion modeling is proposed in Ref [10]. It has been shown that not all individual forecasting models can be used to form the combined model [11]. However, there are many indexes for model evaluation. Because a single evaluation index can only reflect limited aspects of the individual models, the results of model evaluation may be incomprehensive and influence the choice of models. This paper proposes a new model evaluation method with multi-index fusion. Since each index has different reliability and importance in the evaluation, it is necessary to assign different weight coefficients for different indexes. In a previous paper, a method was proposed to calculate the weight coefficient by combining objective weight with subjective correction [12]. In this paper, we investigate using evolutionary algorithms to optimize weights for different evaluation indexes in order to rank models that best predict wind power.

2. Wind Power Forecasting Models

2.1. Least Squares Support Vector Machine M_1

Least squares support vector machine (LS-SVM) is a modified form of SVM [13]. It can better deal with higher dimensional small samples, nonlinear modeling problems, and reduce the computational complexity. With regard to the existing problems of LS-SVM (its parameters are difficult to define), the improved LS-SVM wind power forecasting model based on the coupled simulated annealing-simplex is proposed in order to enhance forecasting accuracy [14]. The simulations in this study were run in MATLAB using LS-SVM toolbox [15].

2.2. Multivariate Linear Regression M_2

The variation in wind power is usually caused by the change of wind speed and its complex interaction with other variables. In addition, many nonlinear problems can be converted to linear regression in statistical regression analysis. Multivariate linear regression along with support vector regression has been used to predict wind power densities in a recent study [16]. In this paper, the MATLAB function *mvregress*( ) is used to fit the multivariate linear regression model.