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A novel hybrid model for bi-objective short-term electric load forecasting

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ABSTRACT

Context: Current decision development in electricity market needs a variety of forecasting techniques to analysis the nature of electric load series. And the interpretability and forecasting accuracy of the electric load series are two main objectives when establishing the load forecasting model.

Objective: Considering that electric load series exhibit repeating seasonal cycles at different level (daily, weekly and annual seasonality), this paper concerns the interpretability of these seasonal cycles and the forecasting accuracy.

Method: For the above proposes, the author firstly introduces a multiple linear regression model that involves treating all the seasonal cycles as the input attributes. The result helps the managers to interpret the series structure with multiple seasonal cycles. To improve the forecasting accuracy, a support vector regression model based on optimal training subset (OTS) and adaptive particle swarm optimization (APSO) algorithm is established to forecast the residual series. Thus, a novel hybrid model combining the proposed linear regression model and support vector regression model is built to achieve the above bi-objective short-term load forecasting.

Results: The effectiveness of the hybrid model is evaluated by an electrical load forecasting in California electricity market. The proposed modeling algorithm generates not only the seasonal cycle's decomposition for the time series, but also better accuracy predictions.

Conclusion: It is concluded that the hybrid model provides a very powerful tool of easy implementation for bi-objective short-term electric load forecasting.

Introduction

Electricity is an energy source that cannot be stored. Effective decisions should be made in time to manage the process of electrical production, distribution and consumption. Current decision development utilizes a variety of forecasting techniques to analysis the nature of electric load series. Therefore, the study of electric load forecasts is of critical importance.

Researchers have proposed many forecasting models on electric load over the past two decades. Chui et al. introduce a multivariate analysis model for long-term load forecasting by selecting three independent variables economic, demographic and climatic [1], while Goia et al. establish a peak load forecasting model using past heating demand data in a district-heating system [2]. Disadvantage of these approaches is that influential independent variables are difficult to determine, and the selection of them determines the forecasting accuracy directly. Therefore, the selection is very important, and is an arduous project also. In contrast, time series models are widely used in electric load forecasting, its theory is that the load series can reflect its future evolution [3–6].

Various artificial intelligence models have been introduced to the time series forecasting, which have extremely high forecasting accuracy usually [7]. Hippert, Kandil et al. present short-term load forecasting models by the application of artificial neural networks (ANN) to model load dynamics [8,9]. To improve the forecasting performance, Niu et al. propose a hybrid ANN model by combining some statistical methods [10]. However, ANN is an incomprehensible black-box modeling process and goes to over-learning easily. For this reason, fuzzy logic methods have been combined with the forecasting models to improve the performance of ANN [11,12]. Considering that support vector regression (SVR) applies the structural risk minimization principle to minimize an upper bound of the generalization errors, rather than minimizing the training errors which are used by ANNs, SVR is shown to be very resistant to the over-learning problem, eventually achieving a high generalization performance [13]. Alenezi et al. develop a support vector regression model for real-time flowtime prediction by examining several combinations of kernel and loss functions [14].

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Hong presents a SVR model with immune algorithm (IA) to forecast the electric loads [15]. Recently, Conforti and Guido obtain the optimal linear combination of known kernel matrices by using a semidefinite programming approach, and this kernel based support vector machine has been applied to some medical diagnostic decision making problems [16]. To sum up, the goals of the above studies are to consider the interpretability and accuracy of the proposed forecasting model.

In this paper, the author propose a novel hybrid model to consider the above two forecasting goals with respect to the short-term electric load time series under consideration. An important feature of short-term electric load time series is the presence of both an intraweek seasonal cycle and an intraday seasonal cycle [17]. This seasonal term is an effective way to interpret the series structure. To extract the knowledge of seasonal cycles, a multiple linear regression model that involves treating all the seasonal cycles as the input attributes is established. The multiple linear regression model has advantages of simple feature and strong interpretability, but fail to the load forecasting of nonlinear part. Modeling the nonlinear part is a difficult task. For instance, over-fitting may happen if a special time is not a regularity and is a temporary phenomenon. These special timings are not always fixed and move over time and will require re-calibration of system to maintain fidelity. To solve the problem, a SVR model based on optimal training subset (OTS) and adaptive particle swarm optimization (APSO) algorithm is combined to model the nonlinear part of the load series. As the load series can reflect its future evolution, and SVR model has attractive features and profound empirical performance for nonlinearity data application [18], thus improving the forecasting accuracy of the above load linear regression model. Finally, the case study and model residual test are implemented to demonstrate the performance of the proposed hybrid model. For a clearer illustration, the block diagram of the novel hybrid model is shown in Fig. 1.

The paper is organized as follows. Section "Multiple linear regression model for seasonal cycles time series" introduces the multiple linear regression for electric load series. Then, the parameters' meaning behind the proposed regression model is explained. Section "Support vector regression" describes the basic idea of support vector regression (SVR). The hybrid model is proposed in Section "The proposed hybrid model". Section "Experiments" shows and discusses the experimental results for the real case. A brief review of this paper and the future research are discussed in Section "Conclusion".

Multiple linear regression model for seasonal cycles time series

In this paper, the author uses the electric load series in California electricity market to illustrate the implementation of the hybrid model and compare the forecast accuracy of the various models. Fig. 2 shows the short-term electric load series from April 1, 1998 to April 30, 1998. An important feature of this electric load time series is the presence of both an intraweek seasonal cycle and an intraday seasonal cycle, while the annual seasonal cycle can be considered for long-term time series. This feature is an effective way to interpret the series structure. To extract the knowledge of seasonal cycles, a multiple linear regression model (MLR) that involves treating all the seasonal cycles as the input attributes is established.

The number of seasonal cycles includes the m_1 periods of the intraday cycle and the m_2 periods of the intraweek cycle. For hourly load data, this amounts to $m_1 + m_2 = 24 + 24 \cdot 7 = 172$ terms. This number of seasonal cycles can be reduced by analyzing the feature of the load series [19]. A common intraweek cycle is used for all the days of the week, then an interaction occurs when the effect of some periods of a day is significantly modified by other periods of the day. Therefore, some interaction terms should be added for the periods of the days that exhibit different patterns of load. For each period of the seven days of the week, the average load of Australian is given as shown in Fig. 3. The following observations can be made from Fig. 3.

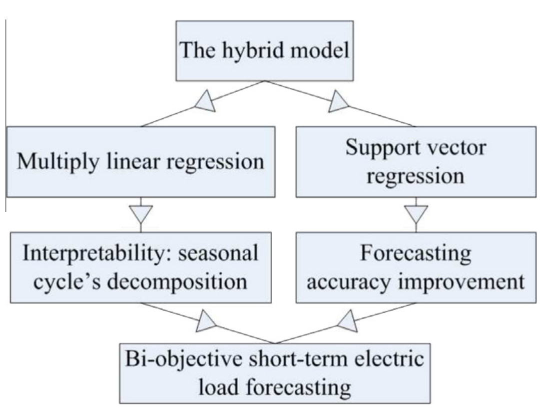

Fig. 1. The block diagram of the novel hybrid model for bi-objective short-term electric load forecasting.

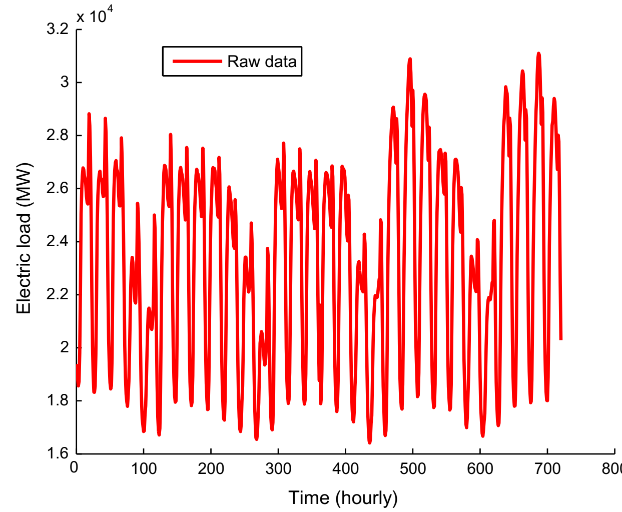

Fig. 2. Hourly electric load in California electricity market for about four-week period from April 1, 1998 to April 30, 1998. Each week contains $7 \times 24 = 168$ periods.

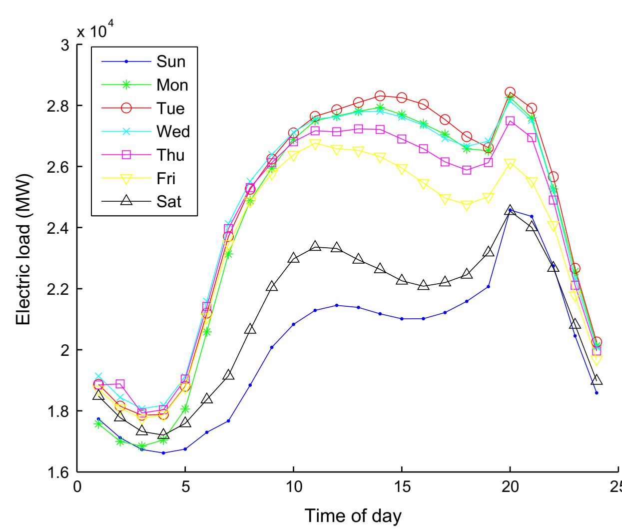

Fig. 3. Average intraday cycle for each day of the week in California electricity market. (It is computed using the sample of Fig. 2.)