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Online electricity demand forecasting based on an effective forecast combination methodology

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ABSTRACT

This paper presents a new forecast combination methodology for generating very short-term electricity demand predictions under both normal and anomalous load conditions. The main contribution of the work is to propose an online load forecasting system that has the ability to achieve good forecasting accuracy, avoid large forecasting errors and ensure low computation time. The real-time load data from the French power system and the Australian dataset for the state of New South Wales are used as an illustrative example to evaluate the performance of the proposed methodology. The results reflect that the developed approach has better forecasting performance than other methods considered in this study. For example, the results from the public holidays in France showed an average mean absolute percentage error (MAPE) of 0.863%, and the accuracy improvements over a simple average combination method, the best individual method, and a weighted combination are 15.887%, 13.353%, and 3.034%, respectively. For the case of the Australian load dataset, our forecasting system achieved an average MAPE of 0.860% and the improvement in comparison to a benchmark algorithm from the literature is equal to 8.316%.

1. Introduction

Electricity demand forecasting is the primary prerequisite for achieving the goal of sustainable energy management and economic and secure operation of modern power systems. The task of knowing the electricity demand in advance is needed to sustain supply/demand balance and to manage the process of electricity production, distribution and consumption on a variety of temporal scales: very short-term from few minutes to an hour, short-term from an hour to one week [1–5], medium-term from one week to one year [6–9], and long-term from one year to decades [10–12]. In particular, the accurate very short-term load forecasts (VSTLF) are needed for the real-time scheduling of electricity generation as well as load-frequency control and economic dispatch functions. With the deregulation of electricity markets and the growing penetration of renewable energy sources into the energy matrix of today's power networks, such predictions are also of importance to market participants to mitigate the effects of renewable energy sources intermittence on grid stability and reliability.

Over the past few years, researchers have studied this problem of improving VSTLF accuracy and various classical and artificial intelligence techniques have been considered using different simulated datasets. Classical methods include Box–Jenkins time series models [13,14], exponential smoothing [15,16], and Kalman filtering [17,18]. Artificial intelligence techniques include neural network [19–21], fuzzy logic [13], adaptive neuro-fuzzy inference system [22,23], and support vector regression [24]. Hybrid methods can be also used to combine the advantages of several algorithms. A typical way to create a hybrid model is to use the empirical mode decomposition as a tool for decomposing the electric load time series into a limited number of intrinsic mode function components, and to forecast the decomposed sequences with appropriate computational intelligence models. However, the application of empirical mode decomposition requires a significant execution time and the forecaster may face difficulty to handle the mode-mixing problem, since the components of new time series may significantly differ from those used while training the forecasting models [25]. In the other hand, wavelet decomposition is an efficient technique to unfold the inner features of the electric load time series. In this manner, many recent papers discussed the

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use of wavelet transform to decompose the data into constitutive series that can be predicted more accurately than the original signal [26].

However, it is not an easy task to perform the accurate predictions of electricity consumption, since the electricity demand behavior is complex and the load time series is non-stationary in mean and variance, containing long run trend, multiple cycles of seasonal fluctuations as well as random noise [27,28]. In fact, there is not any forecasting method which gives the best result for all times: some approaches may perform very well under certain circumstances, and they fail to reflect the variation laws and power load information in others [29]. Hence, the methodology of forecast combination, also called ensemble forecasting, is a suitable tool which has been successfully applied in many disciplines for improving forecasting accuracy [30,31].

New studies related to electric load forecasting research area show that the strategy of combining different models is quite useful to improve the forecasting performance. The simplest way to combine forecasts is to assign equal weights to the individual forecasts. This method often work reasonably well when we are uncertain about which method is best. So practically, one can make important performance improvements in electric load forecasting by simply averaging the forecasts. In the study given by Taylor [15], a variety of forecasting methods have been evaluated using minute-by-minute British electricity demand data, and the results showed that the simple average of the forecasts from the weather-based approach and the double seasonal Holt-Winters-Taylor (HWT) method resulted in forecasts that outperformed all other methods beyond about an hour ahead. Another popular method for combining forecasts is the unequal weighting based on the past forecast performance of models. In the approach proposed in [32], the short-term load is obtained by combining the forecasts generated by the seasonal autoregressive integrated moving average (SARIMA) and the neural networks models, and the weights of the combination are determined using a variance–covariance approach. The results of this study showed an important improvement in forecasting accuracy compared to other methods. A combined short-term load forecasting model based on ensemble empirical mode decomposition (EEMD) and sub-section particle swarm optimization (SS-PSO) is proposed in [33]. Firstly, the load sequence is decomposed into a limited number of intrinsic mode function (IMF) components and one remainder by EEMD. Then, the decomposed sequences are forecasted with appropriate forecasting models. SS-PSO is proposed and used to optimize the linear combination weights. The numerical results indicate that the proposed method in this reference paper gets a higher forecasting accuracy rate when compared with other forecasting techniques. A number of recent research studies have suggested also the use of forecasts combination as a promising tool for improving the electricity demand forecasting performance [34–36].

However, the combined models cited above have the drawback of ignoring the effect of large forecasting errors. Actually, most of the existing methods in the literature of electric load forecasting focus only to evaluate the performance in normal and typical conditions and they often ignore the effect of the anomalous load that occurs on special days (such as the case of public holidays). For example, if a combined model constructed by a weighted combination is implemented to forecast the load of a particular public holiday, a poor estimation could be obtained at the case where a large forecasting error is obtained by the individual method that had a higher weight. This poor estimation can be attributed to the dissimilar load behaviors of holidays compared with those of normal days. In addition, for a given special day, the pattern of the load can vary from year to year, depending on the day and season of the year when the abnormal load is occurred. So making an accurate abnormal load forecasting model is a more complicated task compared to the case of constructing a normal load forecasting model.

There have been few research studies for developing accurate load forecasting techniques for special days. Some of them give more attention to the quality of the load data and the rigor of time series analysis. Some other papers aim to provide the appropriate output from a combination of forecasts. While some other works, like the study performed by Ghofrani et al. [37], focus on the consideration of both the appropriate combination of different forecasts and the capture of the most relevant information of the time series as two key elements to perform the task of improving the forecast accuracy of special daily conditions. One of the existing methods in the literature that focus on the quality of the data to predict the atypical load is the triple seasonal exponential smoothing method developed by Arora and Taylor in [38]. The methodological contribution of the authors work is to show how the exponential smoothing method can be adapted to model the load for special days, when used in conjunction with an approach based on rules. The results of the study showed that the advantage of this rule-based method is located on its ability to model normal and abnormal load in a unified framework. However, this model is too complicated, requires a significant amount of load data, and a forecaster intervention is almost essential to restructure the model. In another study, a research work to improve the short-term load forecasting for anomalous load conditions has been presented [39]. The method of this study uses artificial neural network (ANN) models to provide the forecast scaled load curve, and fuzzy inference models to forecast maximum and minimum loads of the special day. The 24 hourly forecast loads of the special day are predicted by combining the results of the ANN and the fuzzy inference method. The benefit of this hybrid structure was to utilize the advantages of both, i.e., the generalization capability of ANN and the ability of fuzzy inference for handling and formalizing the experience and knowledge of the forecasters. The test results showed that the hybrid forecasting method could provide a considerable improvement of the forecasting accuracy for the special days. In Ref. [40] Ghayekhloo et al. presented a hybrid load forecasting framework with a data preprocessing algorithm to enhance the forecasting accuracy. The data preprocessing method is a combination of the input selection, wavelet decomposition and a novel standardization to provide the most appropriate inputs for the Bayesian neural network algorithms. Genetic algorithm is used to optimize the weighting coefficients of different forecast components and minimize the forecast error. The performance and accuracy of this short-term load forecasting method have been evaluated using New England load data. The results from this study showed a significant improvement in the forecast accuracy when compared to other existing techniques.

However, we would point out that most of the forecasting methods in the literature have been implemented off-line using simulated datasets. In fact, the good use of any load forecasting algorithm in practice not only requires the consideration of reasonable accuracy, but requires also the consideration of many other issues, such as the online adaptation ability, the simplicity of use and the computational efficiency. This is particularly important for the case where the lead time is as short as few minutes ahead and the adopted method is a forecast combination. To our knowledge, there is a lack of works that discuss the use of combined methods for a practical application of very short-term load forecasting. This lack has motivated us to provide the present work to the development of an appropriate online load forecasting method that can ensure low computation time and achieve good forecasting performance on both normal and special daily conditions.

The main objective of this paper is to present a new forecast combination method, namely HFCM (Hampel filter-based Forecast Combination Method), for performing the online predictions of the