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A combined model based on multiple seasonal patterns and modified firefly algorithm for electrical load forecasting

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HIGHLIGHTS

- Improve the accuracy and stability significantly of electrical power forecasting.
- Propose a combined model based on several artificial neural networks.
- Use multiple seasonal patterns to pre-process data.
- Modify firefly algorithm with BFGS to improve optimized performance.

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ABSTRACT

Short-term load forecasting (STLF) plays an irreplaceable role in the efficient management of electric systems. Particularly in the electricity market and industry, accurate forecasting could provide effective future plans and economic operations for operators of utilities and power systems. Hence, a more precise and stable load-forecasting model is essentially needed in the field of electricity load forecasting. To avoid the limitations of individual models, a new combined model is proposed. In this model, except for the multiple seasonal patterns used to reduce interferences from the original data, a new optimization algorithm is presented and applied to optimize the weight coefficients of the combined model based on non-positive constraint combination theory. To estimate the forecasting ability of the proposed combined model, half-hourly electricity power data from New South Wales, the State of Victoria and the State of Queensland in Australia were used in this paper as a case study. In the numerical experiments, compared with other six single models, the average mean absolute percent errors (MAPEs) of the combined model were reduced by 0.7138%, 1.0281%, 4.8394%, 0.9239%, 9.6316% and 7.3367%, respectively.

1. Introduction

Short-term load forecasting (STLF) plays a key role in the operation of power systems [1,2]. Many operating decisions are made based on load forecasts, such as maintenance plans and security and reliability analyses for generators, price and income elasticities, and the dispatch scheduling of generating production [3]. Accurate load forecasting can provide sufficient information for market operators who determine day-ahead market prices and relational participants who prepare bids. Inaccurate forecasting results in considerable loss for electric power companies. The relevant literature suggests that operating costs will increase by 10 million due to a 1% increase in forecasting error [4], and the reliability of the power system is sensitive to the error between the actual and forecasted loads. For overload forecasts, the sub-optimal scheduling of power-unit commitments leads to start-up and fixed costs. For under-load forecasts, optimal electricity generation could be required to guarantee the supply, leading to purchases of expensive peaking power [5]. Thus, the development of a robust, accurate and simple load-forecasting technique is highly desirable.

Load-forecasting algorithms can be divided into traditional algorithms and modern intelligent algorithms [6–8]. Traditional algorithms are based on mathematical statistics and include the Kalman filtering method [9], auto-regressive integrated moving average (ARIMA) [10], the regression analysis method [9], exponential soothing [11], the state-space model [12], Box–Jenkins models [13], etc.

For non-linear time series, better performance has been achieved by modern intelligent forecasting algorithms [14–19]. The process from inputs to outputs does not require a quantitative

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correlation or complicated mathematical formulations. Intelligent algorithms have been widely applied in STLF because of their effective employment in ambiguous processes (such as load-time series) [20,21]. For example, artificial neural networks (ANNs) [22–24], fuzzy logic [25,26], support vector machines [27] and expert systems (ES) [28] have been applied in the load-forecasting area. Additionally, two fundamental characteristics of network management, stability and plasticity, characterize the network with fast convergence and stable learning [29]. The application of ANNs to short-term load forecasting has received considerable attention.

In the past two decades, many models have been proposed in the area of time series-based forecasting. Examples include grey forecasting models, artificial neural networks, linear regression and expert systems. However, each method has unavoidable defects, and the desired accuracy level cannot always be provided. For example, non-linear and seasonal characteristics cannot be captured by linear regression. Locally optimal but not globally optimal solutions are more likely to be returned by artificial neural networks. The grey forecasting model can merely effectively work out a certain problem with exponential growth trends, and expert systems are not independent of the knowledge database. It is rare for every individual forecasting model to perform excellently in all cases due to their own particular strengths and weaknesses [30]. Therefore, multiple forecasting models have been proposed to take advantage of each model; these combined methods and hybrid models are considered advanced methods [31,32].

The forecasting combination, which started with Bates and Granger [33], has long been considered an efficient and simple way to perfect forecasting stability, representing an improvement over individual models. It was further developed by Diebold and Pauly [34] and Pesaran and Timmermann [35]. To take advantage of each individual model's strengths and to improve on their disadvantages, different varieties of artificial neural networks (ANN) have been combined to forecast electric power [36,37].

Recently, many articles [38–40] have discussed how to determine the weights of combination forecasts, and the introduced methods are based on the positive weight determination. To achieve better forecasting performance, a novel combined model theory based on the non-positive constraint theory, which was developed by Xiao [41], is applied to this paper. Meanwhile many evolutional optimization algorithms are also used to help determine the parameters of a forecasting model in recent years. Liu et al. [38] used the particle swarm optimization (PSO) to set parameters of a forecasting model for short-term load forecasting of micro-grids. Wang et al. [39] developed a combined model for electric load forecasting based on weight coefficients optimization with the adaptive PSO. Xiao et al. [40] applied the cuckoo search algorithm to determine the weight coefficients of a combined model for electrical load forecasting. In this paper, the Broyden–Fletcher–Goldfarb–Shanno-Firefly Algorithm (BFGS-FA), which is an evolution-based optimization technique, is proposed to set the weight coefficients of the combined model.

Yang [42,43] presented a search algorithm based on population, the firefly algorithm (FA), inspired by the flashing performance of fireflies. FA has been successfully applied to address non-convex and nonlinear optimization problems [44,45]. As indicated by recent studies, FA is easily accessible and outperforms other meta-heuristic algorithms. Comparisons between FA and PSO, bacteria foraging (BF) and artificial bee colony (ABC) algorithms [46–48] show that FA is superior to the other three algorithms.

In recent years, many new modifications have been introduced to improve the performance of the firefly algorithm in optimized problems, including the elitist, binary, firefly, Gaussian, Lévy flight, parallelized firefly and chaos-based firefly algorithms [49,50]. Although each of these modifications to the firefly algorithm has optimized its ability, modifications have not been applied to optimize the weight coefficients of combined models. This study aimed to improve both the exploration and exploitation capacities of the firefly algorithm and to avoid the weakness of the local optima searching ability, such as in the cuckoo search algorithm. Based on the BFGS quasi-Newton method, a new modification of FA was developed to improve the variety of fireflies in the population. When the convergence criterion was increased, as a drawback, the individual fireflies were easily trapped in local optima, a possibility that was decreased with this modified algorithm. To test the proposed algorithm to reach a satisfying performance and feasibility, four testing functions were used. The weighting coefficients of the individual models were determined by the proposed algorithm for forecasting based on the practical daily load data of New South Wales, Queensland and Victoria in Australia.

A time series may contain multiple seasonal cycles of different lengths. The electric load data of New South Wales from 2006 to 2008, shown in Fig. 1, exhibit both daily and weekly cycles. Several notable features are shown. The daily cycles are not all the same, but the cycles for Monday through Friday are similar. Those for Saturday and Sunday are obviously different. Furthermore, the daily cycles may be highly correlated with the levels of the previous day, but they vary with the change in weeks. Therefore, it is necessary to develop an efficient time-series model to identify these principal features that may not impose excessively heavy inferential or computational burdens.

This paper proposes a new combined model that integrates multiple seasonal patterns, several neural networks, non-positive constraint theory and BFGS-FA. Half-hourly electricity power data from New South Wales, the State of Queensland and the State of Victoria in Australia are employed to test the developed model. Based on a series of experiments and analyses, the performance of the combined model was excellent compared to the other four single models. Thus, the combined model, which can be used to forecast the electric load, is helpful for electrical power scheduling to produce various benefits, such as avoiding a power-grid collapse, saving on economic dispatching, reducing production costs and reducing the spinning reserve capacity of thermal power units. This model is also useful in making electric companies' decision in practice. The combined forecasting model, which has high precision, is a promising model for use in the future. In addition, the developed combined model can be utilized in other forecasting fields, such as product sales forecasting, tourism demand forecasting, early warning and flood forecasting, wind speed forecasting, and traffic-flow forecasting.

The rest of the paper is organized as follows. Section 2 introduces individual forecasting models the combined model based on the BPNN, the GABPNN, the GRNN and the WNN and the combined forecasting model theory. Section 3 describes BFGS, firefly algorithm and BFGS-FA which is used to determine weight coefficients of combined forecasting model. Section 4 presents multiple seasonal patterns, some forecasting performance metrics and the forecasting results of individual models. The forecasting results of the proposed combined model and comparisons are discussed in Section 5. Finally, Section 6 concludes the paper.

2. Forecasting models

In this paper, the proposed combined model, based on the non-positive constraint theory, is integrated with four single artificial neural networks.

2.1. Single forecasting models

There are many artificial neural networks that can be applied in electrical load forecasting. In this paper, four single artificial neural