Applied Mathematical Modelling 39 (2015) 2617–2632

Contents lists available at ScienceDirect

Applied Mathematical Modelling

journal homepage: www.elsevier.com/locate/apm

A hybrid application algorithm based on the support vector machine and artificial intelligence: An example of electric load forecasting

Yanhua Chen *, Yi Yang, Chaoqun Liu, Caihong Li, Lian Li

School of Information Science and Engineering, Lanzhou University, Lanzhou 730000, PR China

ARTICLE INFO

Article history:
Received 7 November 2013
Received in revised form 8 August 2014
Accepted 17 October 2014
Available online 22 November 2014

Keywords:
Electric load forecasting
Empirical mode decomposition
Seasonal adjustment
PSO
LSSVM

ABSTRACT

Accurate electric load forecasting could prove to be a very useful tool for all market participants in electricity markets. Because it can not only help power producers and consumers make their plans but also can maximize their profits. In this paper, a new combined forecasting method (ESPLSSVM) based on empirical mode decomposition, seasonal adjustment, particle swarm optimization (PSO) and least squares support vector machine (LSSVM) model is proposed. In the electric market, noise signals usually affect the forecasting accuracy, which were caused by different erratic factors. First of all, ESPLSSVM uses an empirical mode decomposition-based signal filtering method to reduce the influence of noise signals. Secondly, ESPLSSVM eliminates the seasonal components from the de-noised resulting series and then it models the resultant series using the LSSVM which is optimized by PSO (PLSSVM). Finally, by multiplying the seasonal indexes by the PLSSVM forecasts, ESPLSSVM acquires the final forecasting result. The effectiveness of the presented method is examined by comparing with different methods including basic LSSVM (LSSVM), empirical mode decomposition-based signal filtering method processed by LSSVM (ELSSVM) and seasonal adjustment processed by LSSVM (SLSSVM). Case studies show ESPLSSVM performed better than the other three load forecasting approaches.

1. Introduction

With the improvement of people's living standard, people are consuming more and more oil, coal, natural gas and other natural energies. As a result, the nation of China is facing a shortage of natural resources, so it is very important to develop a reasonable energy saving plan. Electricity is one of the most important energy sources in people's life. It plays a more and more significant role in economic development, and its application has attracted particular attention in recent years. However, due to the huge usage of electricity, the big data generated by the electric load and real time required by electricity, make the electric load difficult to store in real life. In addition, the electric load is always influenced by various factors, including weather conditions, social and economic environments, dynamic electricity prices and more. Therefore, in the power system, the electric load is difficult to forecast and remains an enormous problem. The goal of electric load forecasting is to take advantage of every model used and find a balance between production and consumption. In the electricity market, precise electricity demand forecasting is often needed and is fundamental in many applications, for example supplying

* Corresponding author.
E-mail address: chenyh2011@lzu.edu.cn (Y. Chen).

http://dx.doi.org/10.1016/j.apm.2014.10.065

energy transfer scheduling, system security, and management [1]. With an accurate, quick, simple and robust electric load forecasting method, essential operating functions such as load dispatch, unit commitment, reliability analysis and unit maintenance can be operated more effectively [2]. On the contrary, inaccurate load forecasting increases the cost of a utility corporation, and with an inaccurate load forecasting, power consumers cannot reasonably adjust the use of electricity. Thus, developing a method to improve the accuracy of electric load forecasting is essential.

During the past several decades, a wide variety of models have been implemented for electric load forecasting. For example, on the basis of the fuzzy logic system, Yang et al. [3] applied the Wang–Mendel (WM) method for short-term electric load forecasting. Lou and Dong [4] proposed the T2SDSA-FNN (Type-2 Self- Developing and Self-Adaptive Fuzzy Neural Networks) model. Kucukali and Baris [5] used the fuzzy logic approach to forecast short-term electricity demand in Turkey. On the basis of the time-series method, Wang et al. [6] applied the chaotic time series method based on PSO and trend adjustment for the electricity demand forecasting in New South Wales. Vilar et al. [7] used the nonparametric functional method to forecast electricity demand and price in Spain. On the basis of the decomposition method, Wang et al. [8] decomposed the electricity demand data of Queensland, Victoria, and the South East Queensland region into a number of components according to seasonality and day of week. Abu-Shikhah and Elkarmi [9] used the singular value decomposition method to disintegrate the electric load data of the Jordanian power system. While these methods (fuzzy logic system, time series, and decomposition method) improved the forecasting accuracy in their aspects, they could not yield the desired accuracy in all electric load forecasting. Just like Moghram and Rahman [10] concluded, there is no one best method, under all specific situations that can yield a better forecasting accuracy. As a result, the concept of combination and hybrid models were developed.

The combination and hybrid models sum up the merit of two, three or more models, which were first used by Bates et al. [11]. Later, Dickinson [12] proved the fact that the mean absolute error of the combination and hybrid model is lower than that of an individual model, which means combination and hybrid models perform better than the individual model. Then combination and hybrid models were widely used in many applications, such as, a combination model based on the generalized regression neural network with the fruit fly optimization algorithm was proposed by Li et al. [13]. It was used to forecast the electricity consumption of Beijing and the cities of China. Zhang et al. [14] used a new hybrid method of a chaotic genetic algorithm-simulated annealing and support vector regression to forecast the electric load of Northeast China. Other combination models included: combining artificial neural networks and the fuzzy neural network with other models [15–18], which predicted electricity demand in different regions. All of them were verified by real data to prove the effectiveness of the combination method. However, the traditional neural network and the fuzzy neural network methods have several drawbacks. They have restrictions on generalization ability, can easily to fall into a local minimum, and they are unstable in training results which usually requires a large sample. The cause of these drawbacks were due to the optimization algorithms used to select the parameters as well as the statistical measures used to choose the model in the neural network and the fuzzy neural network. Compared with the traditional neural network, support vector machine (SVM) is a new solution in machine learning fields. Instead of using the principle of empirical risk minimization (ERM), SVM uses the principle of structural risk minimization (SRM). In addition ERM minimizes the error on the training data, whereas SRM simultaneously minimizes the empirical error and model complexity, which can increase the generalization capacity of the SVM for classification or regression problems in a lot of training. Compared with the widely used methods for regression problems, such as: one-dimensional linear regression, multiple linear regression and neural network approach, SVM possesses a concise mathematical form and shows many advantages. Besides, SVM can effectively solve the practical problems of small sample size, non-linearity, high dimension and local minimum point. In paper [19], the author applied SVM, optimal training subset and adaptive particle swarm optimization to forecast the electric load in California. However, when solving large sample problems, SVM faced some problems. For example: quadratic programming problem. Least squares support vector machine is the improvement of SVM, compared with SVM, it has the following advantage: use equality constraints to instead of the inequality in standard SVM, solve a set of linear equations instead of quadratic programming. However, single LSSVM model did not get a preferable result, because the selection of the parameters in a LSSVM model was very random and uncertain. And it still lacked systemic methods for the parameters selection. Then Hong [20] used the chaotic particle swarm optimization algorithm to optimize the parameters of support vector regression (SVR) [20]. Wang et al. [21] used the adaptive particle swarm optimization to determine the parameters for the chaotic system. Shayeghi and Ghasemi used applied chaotic gravitational search algorithm to optimize the parameters of LSSVM [22]. Xu and Chen applied the improved particle swarm optimization algorithm to optimize the parameters of LSSVM [23]. Among the LSSVM parameters optimization algorithms, PSO can save time and is very efficient in searching suitable parameters of a LSSVM model, so this paper used the PSO to optimize the parameters of LSSVM, namely PLSSVM [24].

Though the above-mentioned methods can generate a sufficiently accurate prediction for different cases, in general, they have concentrated on the accuracy improvement of the models acquired without paying attention to the internal characteristics of the data. In fact, electric load data is usually influenced by unstable factors thus causing noise signals, which increases the difficulty of forecasting. Due to the influence of season, week and month, electric load data often presents periodicity and seasonal components. Considering the noise signal and seasonal aspects of electric load data, not preprocessing the data and directly forecasting the electric load is bound to affect the forecasting accuracy. In this paper, the empirical mode decomposition-based signal filtering method was used to handle the noise signals, and the seasonal adjustment approach was used to eliminate the seasonal factors. First of all, the empirical mode decomposition disintegrates the noise signals into intrinsic oscillatory components called intrinsic mode functions (IMFs) by means of an algorithm referred to as a