Electrical Power and Energy Systems 63 (2014) 64–70

Contents lists available at ScienceDirect

Electrical Power and Energy Systems

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

Mid-term electricity market clearing price forecasting utilizing hybrid support vector machine and auto-regressive moving average with external input

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ARTICLE INFO

Article history:
Received 18 November 2013
Received in revised form 6 May 2014
Accepted 12 May 2014
Available online 24 June 2014

Keywords:
Auto-regressive moving average with external input (ARMAX)
Deregulated electric market
Electricity market clearing price (MCP)
Electricity price forecasting
PJM
Support vector machine (SVM)

ABSTRACT

Currently, there are many techniques available for short-term electricity market clearing price (MCP) forecasting, but very little has been done in the area of mid-term electricity MCP forecasting. Mid-term electricity MCP forecasting has become essential for resources reallocation, maintenance scheduling, bilateral contracting, budgeting and planning purposes. A hybrid mid-term electricity MCP forecasting model combining both support vector machine (SVM) and auto-regressive moving average with external input (ARMAX) modules is presented in this paper. The proposed hybrid model showed improved forecasting accuracy compared to forecasting models using a single SVM, a single least squares support vector machine (LSSVM) and hybrid LSSVM-ARMAX. PJM interconnection data have been utilized to illustrate the proposed model with numerical examples.

Introduction

Electricity market clearing price (MCP) is the price that exists when an electric market is clear of shortage and surplus. It is the final outcome of market bidding price. When electricity MCP is determined, every supplier whose offering price is below or equal to the electricity MCP will be picked up to supply electricity at that hour. They will be paid at the same price, the electricity MCP, not the price they offered. The reason for this is to keep fairness of the market and to avoid market manipulation. The forecasting of electricity MCP is a prediction of future electricity price based on given forecast of electricity demand, temperature, sunshine, fuel cost, precipitation and other related factors. Good electricity MCP forecasting can help suppliers and consumers to prepare their electricity usage and bidding strategy in order to maximize their profits. Offering the appropriate amount of electricity at the right time with the right bidding price is of paramount importance.

Currently in the electricity price forecasting studies, short-term forecasting of the electricity MCP is the most focused research area. It is also commonly known as the 24-h day-ahead electricity price forecasting. Unlike the short-term forecasting, very little work has been done to forecast electricity MCP on a mid-term basis [1–5]. The mid-term forecasting of the electricity MCP focuses on a time frame from one month to six months. It is essential for decision making and mid-term planning purposes such as generation plant expansion and maintenance schedule, reallocation of resources, bilateral contracts, and hedging strategies [5]. The mid-term forecasting of the electricity MCP is different from the shot-term forecasting in many ways. First of all, mid-term forecasting by its nature cannot utilize the trend from the immediate past while the short-term forecasting can. Future segment is not contiguous to the immediate past history for which electricity MCP data are available for the mid-term forecasting of the electricity MCP. In order to accurately forecast the future electricity MCP with segmented input data, the mid-term forecasting model must possess very strong adaptability in handling out-of-sample and segmented data during training phase. Secondly, because of the unavailability of immediate past data, forecasting technique such as time series cannot be utilized in mid-term forecasting. In mid-term electricity price forecasting, each input data at hour t has to be treated independently from its nearby data such as $t-n$ or $t+n$, for n equals 1, 2, 3.... Moreover, locating and predicating peak prices in the mid-term forecasting of the electricity MCP are extremely difficult. As the short-term forecasting can utilize the trend from the immediate past, locating the peak prices in most cases is usually very accurate. The main challenge in short-term forecasting is how

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http://dx.doi.org/10.1016/j.ijepes.2014.05.037

accurately the forecasting model can predict the values at each peak price spot. However, in the mid-term forecasting of the electricity MCP, because of the unavailability of data from the immediate past, locating the peak prices becomes extremely difficult. As a result, accurately predicting the values at peak price spots becomes even more difficult. The fourth difference is the length of historical data that are needed to train the forecasting model. The short-term forecasting of the electricity price model usually only needs the data of the last couple of days to train the forecasting model. On the other hand, the mid-term forecasting model requires one year of historical data in order to train the forecasting model. Finally, only non-linear regression based forecasting models are capable of mid-term forecasting. Linear regression based forecasting models can only be considered as an add-on module in the mid-term forecasting.

So far, most published works are focused on short-term electricity MCP forecasting, commonly known as 24-h day-ahead electricity price forecasting. There are many techniques available for short-term forecasting of electricity MCP. Among these existing methods, regression methods such as auto-regressive integrated moving average (ARIMA) [6], wavelet transform [7–9], Monte Carlo simulation [10], time series [11,12], bid-based stochastic model [10] and dynamic regression [13] were the first generation of techniques utilized to forecast electricity MCP. Later on, artificial neural network (ANN), due to its flexibility in handling highly non-linear relationships and relatively easy implementation [1–3,14,15] was applied to forecast short-term electricity MCP [14–19]. Deregulated electric markets that utilize ANN method to forecast electricity MCP include PJM interconnection, Australian electric market, England-Wales pool and New England ISO [16].

Recently, support vector machine (SVM), a new learning method based on structural risk minimization, has gained increased attention in electricity MCP forecasting [20–23]. The major advantages of SVM over ANN or any other forecasting models are that SVM can avoid problems such as data over fitting, local minimum and unpredictably large out-of-sample data error while at the same time achieving better results. SVM is also a very robust forecasting model. Regardless of the initial value, SVM will always end up with the same acceptable result. Moreover, SVM has less adjustable parameters compared to ANN and therefore, is less complicated in parameter selection. SVM optimizes itself based on the selection of training input data. A traditional SVM could achieve around 3% [5,24] better performance compared to a traditional ANN on the short-term electricity MCP forecasting. Several algorithms are used to improve the training of SVM that in turn improves the price forecasting accuracy. These algorithms include genetic algorithm (GA) [24–27], artificial fish swarm algorithm [28], independent component analysis (ICA) algorithm [29,30], rough sets algorithm [31,32] and time series prediction [33–35]. An upgraded SVM, called the least squares support vector machine (LSSVM) was also developed to improve the accuracy of the original SVM [25,27,36–38]. Although each method has shown some improvements, the overall system accuracy was still quite low.

Electricity MCP forecasting using hybrid models combining several prediction methods is the new trend in recent electricity price prediction studies. Hybrid models can compensate the weaknesses of utilizing any individual established method and achieve better overall system results. Torbaghan et al. [5] proposed hybrid mid-term electricity monthly average price forecasting models combined with SVM/SVM, SVM/NN, NN/SVM and NN/NN. Swief et al. [23] utilized the principle component analysis (PCA) and k nearest neighbor (KNN) points technique to reduce the number of data entry to the SVM model. Li et al. [36] proposed a hybrid electricity price forecasting model that integrates clustering algorithm with LSSVM. Fan et al. [38] proposed a hybrid forecasting model that includes the Bayesian clustering by dynamics (BCD) and SVM where the BCD classifier is applied to cluster the input data set into several subsets in an unsupervised manner. Zhao et al. [39] forecasted the prediction interval of the electricity price utilizing SVM and non-linear conditional heteroscedastic forecasting (NCHF) model. Lira et al. [40] compared several forecasting models including ARMAX, PARMAX, ARX Kalman, ARX particle, NN and TSK in the Columbian day-ahead electricity market. Catalão et al. [41] proposed a hybrid Wavelet-PSO-ANFIS approach for short-term electricity price forecasting. A hybrid Wavelet-NN-Fuzzy logic approach was also proposed by Amjady et al. in [42]. Catalão et al. [43] presented a hybrid real-coded genetic algorithm (RCGA) and neural network (NN) forecasting model. A hybrid feature selection technique and cascaded neuron-evolutionary algorithm (CNEA) is also proposed by Amjady and Keynia in [44].

Based on the success of utilizing hybrid forecasting techniques in predicting short-term electricity MCP, the performance of such techniques under mid-term electricity MCP forecasting is urged to be evaluated. Since machine learning techniques are heavily relying on the training data, will the proposed hybrid model achieve acceptable results under mid-term forecasting environment is of paramount importance. Therefore, a hybrid mid-term electricity MCP forecasting model is presented in this paper to predict hourly electricity MCP for an entire month, six months ahead. The motivation of the proposed work is to evaluate the performance of a hybrid SVM and ARMAX forecasting model in mid-term forecasting under constrains and assumptions that are different from short-term forecasting. The proposed forecasting model contains a SVM module and an auto-regressive moving average with external input (ARMAX) module. The ARMAX method is used as an add-on module to improve the forecasting results obtained by the SVM forecasting module. In this work, it is considered that the forecasting input data are given so that the performance of the presented hybrid forecasting model will not be affected by the inaccurate input variables. Historical data from the PJM interconnection system are used to evaluate the performance of the proposed hybrid forecasting model. Computational results indicated that the proposed hybrid forecasting model can improve the prediction accuracy of price values compared to using a single SVM in mid-term electricity MCP forecasting. The main contribution of this paper can be summarized as: (1) addressing and resolving problems associated with mid-term electricity MCP forecasting, (2) addressing and resolving the problems associated with utilizing a single non-linear regression based forecasting model to forecast mid-term electricity MCP, such as SVM, and (3) presenting a hybrid forecasting model combined with a SVM and an ARMAX modules. The rest of the paper is organized as follows: section ‘Hybrid forecasting model’ describes the SVM and ARMAX modules presented in this paper. The proposed hybrid forecasting model is given in section ‘Hybrid SVM and ARMAX based mid-term electricity market clearing price forecasting’. Case studies are presented in section ‘Case studies’. Conclusions are included in section ‘Conclusions’.

Hybrid forecasting model

Support vector machine

A support vector machine (SVM) is a new learning method based on structural risk minimization. It was first introduced by Vapnik in 1979 based on the statistical learning. At the early stage, SVM was only used for classification purposes. Later on, the regression computation of nonlinear function was added by solving a convex quadratic optimization problem. Multi-class classification can be considered as regression computation with multiple predefined threshold values. Suppose $\{(X_t, y_t)\}$ for $t = 1$ to N is a given set of data where $X_t = (x_{t1}, x_{t2},..., x_{tk})$ is the input vector at time t with k