Weights Optimization Based on Genetic Algorithm for Variable Weight Combination Model of BP-LSSVM for Day-ahead Electricity Price Forecasting

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ABSTRACT: Affected by various factors, the electricity market prices are highly volatile seasonal and stochastic with nonlinear and non-stationary characteristics. The previous literature indicates that improving the accuracy of price forecasting by applying one model alone can be problematic. To evaluate the prices properly and efficiently, this study proposes genetic algorithm (GA)-back propagation neural network (BP)-least square support vector machine (LSSVM) (GA-BP-LSSVM) model. The original prices series are preprocessed to eliminate the outliers, then a BP-LSSVM is built to forecast the prices. In order to determine the weights of this combination model, GA is proposed to optimize the weights. Compared with traditional LSSVM, BPNN and BP-LSSVM, the forecasting results of this proposed model applied to the electricity market of Pennsylvania-New Jersey-Maryland (PJM) suggest the proposed model outperforms other models.

1 GENERAL INSTRUCTIONS

As the traditional vertically integrated electric utility structure deregulated and replaced by a competitive market, the accuracy of day-head price forecasting directly affects the bidding decisions of market competitors and their economic benefits, consequently companies that trade in this market extensive use of price prediction approaches to stay competitive, which maximizes profits and minimizes risks. In addition, residential electricity cost also can be minimized if an accurate price forecast is available, thus, abundant approaches were proposed in the past. Traditional methods of price forecasting mainly based on time series analysis and statistical models, including linear regression model, and auto regressive moving average model [1,2]. However, with the development of artificial intelligence algorithms, the self-learning theory is widely utilized in the field of electricity price forecasting. Artificial neural network (ANN) and genetic algorithm (GA) are the most commonly used algorithms. Amjad N. (2006), due to the randomness and volatility of day-head price, wavelet transform method is also proposed to decompose historical data and establish a multivariate time series model to improve the prediction accuracy. Garcia R.C. (2005), an efficient method based on a new fuzzy neural network is proposed for short-term price forecasting of electricity markets. By combining the fuzzy logic and an efficient learning algorithm, an applicative model is presented for the non-stationary behavior and outliers of the price series. Anbazhagan S (2013), in order to maximize profits, a detailed explanation of GARCH models is presented to predict next-day electricity prices to develop bidding strategies or negotiation skills. Sun W. (2015), in order to realize the day-ahead deregulated electricity market price forecasting a recurrent neural network model is utilized by applying the Elman network, forecasting accuracy can be achieved with less computation time with a nearly state of the art Elman network.

Single model could not meet the increasing requirements of the prediction accuracy. Thus, the research of the combination models is rapidly developing. The superiority of these combination models is to take full advantage of the information of historical data by considering different factors and modeling from different perspectives. Onnen C (1997) the study proposes a method to predict hourly electricity prices for next-day electricity markets by combining methodology of ARIMA and ANN models. Areeku P (2009), ARMA-BPNN is
proposed to solve nonlinear problem, and the experimental results indicate that the proposed model outperforms using single model. Shi S(2013), a hybrid mid-term electricity market clearing price (MCP) forecasting model combining both least squares support vector machine (LSSVM) and auto-regressive moving average with external input (ARMAX) modules is proposed. In the electricity market, day-ahead electricity price is influenced by many uncertain factors, including changes of natural environment, electricity demand, constraints of network operation and bidding strategies of buyers and sellers, which lead the time series of electricity price to inherent non-stationarity and discreteness in practice, even the dynamics and characteristics frequently switch between different segments or regions in the short term. However, the previous literatures may be problematic in following perspectives:

(1) Traditional forecasting methods, such as ARIMA, typically require nonheteroscedasticity, iid, etc. in the time-series, which is difficult to achieve in price forecasting.

(2) Artificial intelligence algorithms can be self-learning, but single forecasting method cannot get the expected effect.

(3) The weights determining of optimal combination algorithms is based on minimizing sum of the squared errors, which may make the weights negative, meanwhile the optimality of weights also can be ensured.

In order to solve the problems mentioned above, the present study weights optimization based on genetic algorithm for variable weight combination model of BP_LSSVM (GA-BP-LSSVM). The choice of the network can be adjusted by the concrete issues, since BP is a mature and simple artificial intelligence. Therefore, determined by deep analysis for day-head prices, the network improves the prediction accuracy. LSSVM not only can solve the fatal problem of local minima, it is also a powerful methodology for solving nonlinear forecasting issues with small samples, taking full advantage of the complementary of these two models. Then by using GA traversing the errors of expected and actual values, with the determined weights of this combination model, the problem of weights determining of optimal combination algorithms can be overcome. This proposed combination model is applied to the electricity market of Pennsylvania-New Jersey-Maryland (PJM). Compared with traditional LSSVM and BPNN and BP-LSSVM, the results indicate that GA-BP-LSSVM outperforms the compared models mentioned before.

The framework of this study is as follows: Section 2 provides the brief description of GA, BPNN and LSSVM; Section 3 presents the framework of the proposed method; Section 4 analyzes an experiment study to validate the proposed method; Section 5 concludes this study.

2 GENERAL BACKGROUND

2.1 Genetic Algorithms (GA)

Genetic algorithms, coding the candidate solutions of an optimization algorithm as a string of characters, are usually binary digits. In accordance with the terminology borrowed from the field of genetics, this bit string is usually considered to be a chromosome. Genetic algorithm optimization process is generally as follows:

Start with the generation of an initial population and code the individuals of an optimization algorithm as a string of characters. Define the size of the population $M$, crossover probability $P_c$, mutation probability $P_m$ and the termination condition; individual is randomly generated as initial population $X(0)$;

1.1 Individual evaluation. Assess the fitness of individuals in $X(k)$;

2.1.2 The evolution of populations

1) The reproduction or selector operator chooses $M/2$ chromosomes according to their fitness for mating;

2) Crossover exchanges genetic material in the form of short allele strings between the parent chromosomes according to the crossover probability $P_c$;

3) Mutation introduces new genetic material by random changes according to the crossover probability $P_m$;

4) The test of termination. If the termination conditions are fitted, the output $X(k+1)$ is the best individual with the max fitness, then the evolution will be stopped; otherwise, return to the step (2).

2.2 BP Neural network

Back Propagation (BP) neural network consists of input layer, hidden layer and output layer. Each layer of neurons is not connected, only the adjacent layers neurons have individual connection.

2.3 Least Square Support Vector Machine (LSSVM)

LSSVM is proposed as an improved algorithm based on support vector machine(SVM), given the training data set $\{x_i, y_i\}_{i=1,2,\cdots,N}$, with the input $x_i \in \mathbb{R}^n$ and the output $y_i \in \mathbb{R}^n$. the following
regression model is constructed by using nonlinear
mapping function \( \phi(x) \)
\[
  f(x) = W^T \phi(x) + b
\]  

Given the training data set \( \{x_i, y_i\} (i = 1, 2, \ldots, N) \), the optimization problem of LSSVM is defined as follows,
\[
  \begin{align*}
  \min_{W, \xi} J(W, \xi) &= \frac{1}{2} W^T W + \frac{C}{2} \sum_{i=1}^{N} \xi_i \\
  \text{s.t. } y_i &= W^T \phi(x_i) + b + \xi_i, \quad i = 1, 2, \ldots, N
  \end{align*}
\]  

Where \( W \) is \( n \)-dimension weight vector; \( \xi \) is the training error; \( C > 0 \) is the punish factor, which determines the trade off between minimizing the training error and minimizing model complexity.

3 METHODOLOGY AND MODELS FOR PRICE FORECASTING

3.1 Data set selection and preparation

Data from 10/9/2014 to 12/9/2014 chosen from the US PJM electricity market is considered to be the original data, and the price changes is hourly analyzed.

The shape of price profiles presents periodical characteristics, which is usually hour cycles. The price profile hourly modified to reflect changes in the electricity market behavior.

Considering the closer price having a great impact on the further one, 5 training samples near the forecasting point are selected as input variable.

Input variable \( X = \begin{bmatrix} x(d+3) \\ x(d+2) \\ x(d+1) \\ x(d) \\ x(d-1) \end{bmatrix} \), where \( x(d,t) \) is the price on the \( d \)-th at time \( t \)-th.

Besides, based on the observation of historical data, the deviated points, caused by random factors, found in the normal time-series could not represent the characteristic of time-series, thus the result of forecasting usually affected without processing.

By the observation of the normal data, a certain relation is presented among these adjacent points in historical data, the difference between the adjacent ones is limited into a certain range. Within this fluctuation range, the points are normal. Otherwise, it is considered to be outlier, which will be eliminated. Eliminating outlier is considered to be data smoothing. In this study, the method of data smoothing is as followed: fluctuation range is defined as \( \theta(0) \), which beyond this range will be considered as outliers.

If \( |x(d,t) - x(d,t-1)|/x(d,t-1) > \theta(0) \), then
\[
  x(d,t) = \frac{x(d,t-1) + x(d,t+1)}{2}
\]

3.2 Modeling Procedure

Set the actual value of a forecast problem at a certain time as \( y(t) (t = 1, 2, \ldots, N) \). This prediction problem has viable methods of \( n \); the predicted value or fitting value of the model is respectively measured \( y_i(t) (i = 1, 2, \ldots, N) \), and set the weighted vectors of \( n \) predict methods as \( W = (W_1, W_2, \ldots, W_n)^T \).

Eventually, the combination forecasting model can be expressed as:
\[
  \hat{y}(t) = \sum_{i=1}^{n} W_i y_i(t)
\]  

Where, \( \hat{y}(t) \) is the \( t \)-th value of combination forecasting model;
\( y_i(t) \) is the \( t \)-th value measured by the \( i \)-th predict method \( (i = 1, 2, \ldots, n) \); \( W_i \) is \( i \)-th weighting coefficient of predict method.
\( y_{LSSVM} \) represents the predictive value of LSSVM, and \( y_{BPNN} \) represents the predictive value of BPNN, so variable weight combination model is as follow:
\[
  \hat{y}(t) = W_1 y_{LSSVM} (t) + W_2 y_{BPNN} (t)
\]  

GA is proposed to determine the weights of \( W_1, W_2 \). The specification of the fitness function is a very important aspect of the design of genetic algorithms, since the solution of the optimization problem and the performance of the algorithm depends on this function. According to the approach presented in this study, the objective function to be minimized is consisted of the absolute error between predictive value and expected value.

\[
  \epsilon_j (t) = |\hat{y}_j (t) - y(t)| = |W_1 y_{LSSVM} (t) + W_2 y_{BPNN} (t) - y(t)|
\]  

As the GA operator is designed to maximize the fitness function, the above minimization problem can be solved by utilizing the following transformation:
\[
  f_j = 1/\epsilon_j (t)
\]
Where \( \varepsilon_j(t) \) is the error between predictive value and expected value; \( y(t) \) is the expected value of price; \( f_j \) is the fitness of \( j \)-th individual.

In this study, based on the ratio of fitness in genetic algorithm selection operation, roulette method is chosen to calculate the fitness. Consequently, the election probability of each individual is \( p_j \):

\[
p_j = \frac{f_j}{\sum_{j=1}^{m} f_j}
\]

(7)

Where, \( m \) is the size of initial population.

Finally, the weight \( W \) of variable weight combination model \( y(t) \) is determined by the genetic operators after \( D \) iterations.

4 ILLUSTRATIVE EXAMPLE

Price forecasting is computed by using historical data from the PJM market of year 2014. The performance of the two compared models, BP and LSSVM.

As the previous description, the performance of this variable weight combination model relies on its weights. Using the outputs \( y_{LSSVM} \) and \( y_{BPNN} \) as the training samples of GA optimization, setting the size of the initial population \( n = 10 \), iteration \( D = 1000 \), crossover probability \( P_c = 0.1 \) and the mutation probability \( P_m = 0.1 \). The results indicate that the average fitness is 28.07, while the algorithm iterates to 289 times, and the best individual is the invariable one in later iterations.

By using MATLAB 2013a, the best individual is determined, which is as \( W = (W_1, W_2) = (0.8485, 0.1062) \)

Then the variable weight combination model is as follows:

\[
y(t) = W_1 y_{LSSVM}(t) + W_2 y_{BPNN}(t)
\]

\[
= 0.8485 y_{LSSVM}(t) + 0.1062 y_{BPNN}(t)
\]

The type of criterion has been adopted to assess and compare the performance of the models: mean absolute percentage error (MAPE), which can be defined as:

\[
MAPE = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{\hat{y}(t) - y(t)}{y(t)} \right| \times 100
\]

(8)

In order to verify the prediction effect of the algorithm, taking the historical data from 10/9/2014 to 12/9/2014 as samples to forecast price of 13/9/2014, the results are shown as Figure 1.

By training through three different models and fitting the sample, results of electricity price forecasting have big difference among different algorithms. GA-BP-LSSVM has the lowest MAPE, only 4.64%, while BPNN has the highest MAPE, up to 8.24%, and the MAPE of LSSVM, respectively 6.83%, is between the above two values. Obviously, the combination model BP-LSSVM based on the weights determining of optimal combination algorithms is better than the two single model. And the number of relative error less than 5% of GA-BP-LSSVM is 17, and the value of which is low. The number of relative error less than 5% of LSSVM is 12. Meanwhile, the prediction of GRNN has a large fluctuation; the vast majority of the relative error is more than 5%; a greater error is between the predicted and actual values, and the forecast is not satisfactory. Therefore, it is proved that GA-BP-LSSVM has a better prediction effect.

Figure 1. The comparison between the prediction results.

5. CONCLUSION

For the periodic, unsteady and fluctuant of the electric price time series in power market, this study proposes an optimized algorithm based on GA-BP-LSSVM, and it is applied to the electricity market of PJM. The results indicate the following conclusions:

(1) GA optimization for weights can reach the global optimum to improve the prediction accuracy greatly.

(2) GA-BP-LSSVM overcomes the shortages of LSSVM and BPNN. Compared with these two models, results of this study indicate that the prediction accuracy is greatly improved by utilizing GA-BP-LSSVM. Therefore, the variable weight combination model is better for day-head electricity price forecasting.
REFERENCES


