International Journal of Control and Automation
Vol. 9, No. 6 (2016), pp.365-378
http//dx.doi.org/10.14257/ijca.2016.9.6.35

A Short Term Load Forecasting Model Using Core Vector Regression Optimized by Memetic Algorithm

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Abstract

In this paper, a new model, core vector regression (CVR) optimized by memetic algorithm (MA), is presented to predict electric daily load. Support vector regression (SVR) has obtained wide focus in recent years to solve nonlinear regression problems in many fields. However, it is limited on large scale dataset problem because of its high time and space complexity. Hence, CVR is proposed to improve the SVR on solving large scale dataset problem. Proper parameters selection of CVR model determines the complexity and accuracy of the model. In this paper, MA is proposed to optimize the parameters of CVR, which is called MA-CVR. Electric load is the time-dependent data which shows recurrent pattern weekly, seasonally and yearly. In this paper, we adopt MA optimization method and choose adaptive parameters dynamically based on time recurrent character of electric load data. Experimental results show that MA-CVR outperforms the existing model optimized by genetic algorithm which is called GA-CVR.

Keywords*: Short term load forecasting (STLF), Support vector regression (SVR), Core vector regression (CVR), Memetic algorithm (MA), Genetic Algorithm (GA)*

1. Introduction

As Economic Globalization continued developing, electric market is moving towards liberalization and privatization. Consumers are free to choose cheaper and more secure power provider. As we know, competitive price, reliable and stable power supply, and efficient operation are crucial to power providers in electric market. By analyzing and predicting load demand of consumers, power providers can obtain important and valuable support for many operating decisions, such as scheduling of power generation, scheduling of fuel purchasing, scheduling of maintenance, and planning of power transaction [1]. Electric utility operator can optimally allocate resources and adjust schedule effectively based on the load prediction. Therefore, the study of the load forecasting is essential.

Load forecasting is not a new topic in electric world. There are three types of load forecasting: short term, medium term and long term forecasting based on time horizon. Generally speaking, long term forecasting contributes to power system planning, and medium term forecasting helps to make maintenance scheduling and fuel purchasing planning, while short term forecasting is serving to conduct power system operation from day to day.

Short term load forecasting (STLF) is the corner stone of the operation of power system. Without it, no electric utility is able to operate economically, safely, reliably and stably. Scholars never stop researching on it. A large number of methods and techniques have been developed and applied in recent two decades. In early stage, timer series model [2,3], and regression model [4,5] are employed. They are stable and efficient. However, these methods are failed to consider the impact of relative factors, such as weather,

ISSN: 2005-4297 IJCA
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holiday, temperature, wind conditions, and so on. They are based on linear assumption while the electric load is nonlinear. So they cannot get high precision results [6].

Later, people focus on seeking for methods that are good at dealing with multi-variables nonlinear regression. Artificial neutral network (ANN) [7, 8] and support vector machine (SVM) [9, 10] are wildly applied to construct the regression to solve the STLF problem. ANN extracts rules from relevant information including daily temperature, day type, and loads of previous days, then derives training rules and transforms the information into mathematical equations. ANN is superior to previous methods. But there are still some disadvantages of the algorithm, those of which are computationally heavy, possible to get trapped into local minima and subjective in selecting model architecture.

Different from ANN, SVM implements a structural risk minimization (SRM) principle instead of empirical risk minimization (ERM) to minimize training error. Compared with ANN, SVM can achieve global optimum in theory. SVM is widely applied in many areas, such as pattern recognition, bio-informatics, and other classified fields. Its extension called support vector regression (SVR) is employed to solve nonlinear regression estimation problems. In a competition hold by EUNITE [11] in 2001, SVR is successfully applied to solve STLF problem and get champion in the competition. However, the characteristics of high time and space complexity of SVM causes it difficult to deal with large scale dataset. To overcome these disadvantages, core vector machine (CVM) is proposed to solve this problem by exploiting 'approximativeness' in the design of SVM implementations [12]. CVM utilizes approximate algorithm for the minimum enclosing ball (MEB) problem, and CVM can decrease time complexity to replace the SVM. In CVM, n is the size of training dataset. CVM's extension for nonlinear regression problem is called core vector regression (CVR).

Besides, research demonstrates that proper parameters selection of SVM plays a crucial role for building a well-fitted SVM model with high accuracy and stability [13]. Presently grid search [14], genetic algorithm (GA) [15] and particle swarm optimization (PSO) [16] are employed to optimize parameters of SVM. Grid search is the most straightforward method while it is computational expensive. GA learns from the evolution hypothesis of Darwin and different genetic functions, *i.e.* crossover and mutation and is proven to be efficient in solving optimization problems. However, GA can easily be entrapped in local optimum. In contrast to GA, PSO has memory to store all good knowledge by all particles. In addition, particles share information with each other. Hence, PSO is widely welcomed because of its simple concept and fast convergence. However, it often suffers from being trapped in local optimum and its performance greatly depends on its parameters as same as GA. So, a new extension of GA, called Memetic algorithm (MA), is proposed to reduce the likelihood of the premature convergence by exploiting individual learning in order to overcome these problems and local improvements in GA, and also it draws wider attention [17].

In this paper, a novel CVR optimized by MA model, called MA-CVR, is proposed to predict next 24 hours' load demand. The remainder of this paper is as follows. Section II analyzes the short term load forecasting problem and its influence factors. Section III explains the proposed MA-CVR model and its procedure. Section IV verifies the proposed model in a case study and analyzes the empirical results. Then discussion is in Section V and conclusion is in the last section.

2. Problem Statement

In the electricity supply industry, it is important to determine future demand for power as far as possible in advance. If accurate estimates can be made for the maximum and minimum load of each hour, day, month, season and year, utility companies can make significant economies in areas such as setting the operating reserve, maintenance scheduling, and fuel inventory management [18].

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Electricity load shows four obvious periodicities including:

I. Similarity among different days' 24 hours

II. Similarity among different weeks' same weekday

III. Similarity among weekdays and weekends separately

IV. Similarity among important holidays of different years

Besides the periodicities described above, the other important feature of short term electricity load is that it is influenced by kinds of environment factors which cause random change of electricity load. Such as season change, weather change, utility maintenance, special events and so on. For example in summer, the electricity load curve trend is similar to temperature curve trend from June 9, 1998 to June 16, 1998.

As mentioned above, time factors, weather data and social activities should be considered when building forecasting model. The time factors include the time of the day, the day of the week, and the month of the year [19]. The load differs on weekday and weekend. Monday and Friday are classified as a same type day and Tuesday, Wednesday and Thursday as another type day because Monday and Friday are closer to weekend. Holiday also have different load pattern. Temperature is the most important factor of weather condition which influences the load. The high temperature in summer and big temperature change will cause high load demand.

So typically the load can be divided into four parts: a base load, a weather dependent load, a special event component, and a random part. It can be expressed with equation as below:

$$L = L_n + L_w + L_s + L_r \tag{1}$$

Where is L the total load, L_n is the normal part of the load, L_w is the weather dependent part load, L_s is the special event part load, and L_r is the random part load.

3. The Proposed Algorithm

3.1. Core Vector Regressions

SVM is one of the most popular machine learning methods. It has been widely applied in numerous classification and regression problems. SVM usually formulated as a quadratic programing (QP) problem, but the existing solution has high time and space complexity which could limit its application on large scale dataset [20]. In order to overcome the problem mentioned, CVM is proposed. CVM uses MEB to solve SVM's quadratic optimization. By utilizing fast approximate algorithm for MEB problem, CVM achieves an asymptotic time complexity which is linear with and space complexity which is independent of the training dataset size.

3.2. Memetic Algorithm

GA is a widely applied population-based Meta heuristic search algorithm for the optimization problem inspired by Darwin's natural evolutionary concepts of nature selection and genetic mechanism. It consists of creating a population of candidate to the optimization problem and applying probabilistic rules to simulate the process of natural evolution, such as inheritance, mutation, selection and crossover [21]. GA can quickly scan a vast solution set and bad proposals while don't affect the end solution negatively because they are simply discarded. However, premature convergence is an inherent character of this classic GA that limits to search numerous solutions in problem domain. So the GA has the risk of finding a sub-optimum solution. MA, as an extension of traditional evolutionary algorithm, integrates the concept of evolution and besides that combines this with local search [22]. MA is inspired by Darwin's notion of a meme defined as a unit of information that reproduces itself when people exchange their ideas. In contrast to gene, memes are typically adapted by people who transmit them before they

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are passed to next generation [23]. Indeed, from general view, MA can be regarded as one (or several) local search procedure(s) acting on a set pop of $|pop| \geq 2$ solutions in a repeated iteration evolution process. Before we explain the procedures of MA, Local search is introduced firstly as following.

Local search: Local search starts from a candidate chromosome, and moves to its neighbors to find a better solution. Usually we increase a random value in specified range on present chromosome to get a neighbor.

Based on definition above, given $F(x)$ is the fitness function where x is the chromosome and the maximum iteration number is q, the procedure of MA can be illustrated as below.

1. Initialization

Generate population $P = \{x_1, ..., x_n\}$ randomly, where $x_i (i = 1, ..., n)$ is the chromosome, n is the population size. Set present iteration count as $t = 0$.

2. Evaluation

Evaluate each chromosome via fitness function $F(x)$, the chromosome with worst fitness is donated by x_{worst}.

3. Local search

Apply local search on each chromosome, if a neighbor with better fitness than the present chromosome, we replace the present chromosome with the neighbor.

4. Crossover

Select a pair of chromosomes x_i, x_j randomly from P, create two new offspring $x_i^{'}$, $x_j^{'}$. Apply local search on $x_i^{'}$ and $x_j^{'}$, add the children to P.

5. Mutation

Keep n chromosomes with the best fitness in P and apply mutation to each chromosome x_i with a probability μ, and apply local search to the new created chromosome.

6. Iteration

Set t=t+1, if t=q, termination and the chromosome with best fitness in current population P is the solution for the optimization problem. Otherwise go back to step 4.

3.3. MA-CVR Model

In order to make an efficient CVR mode, two parameters C and σ^2 (sigma squared) are needed to be carefully selected. The first parameter C determines the trade-offs between the minimization fitting error and the model complexity. The parameter σ^2 is the bandwidth of radial basis function (RBF) kernel. Hence, the purpose of MA-CVR is to find optimum parameters (C, σ^2) yield high accuracy and generalization ability. The proposed MA-CVR model dynamically optimizes these two parameters simultaneously via MA's evolution progress, and then the parameters optimized are provided for CVR to precede prediction. The procedure of MA-CVR model is illustrated as below and the flowchart is shown in Figure 1.

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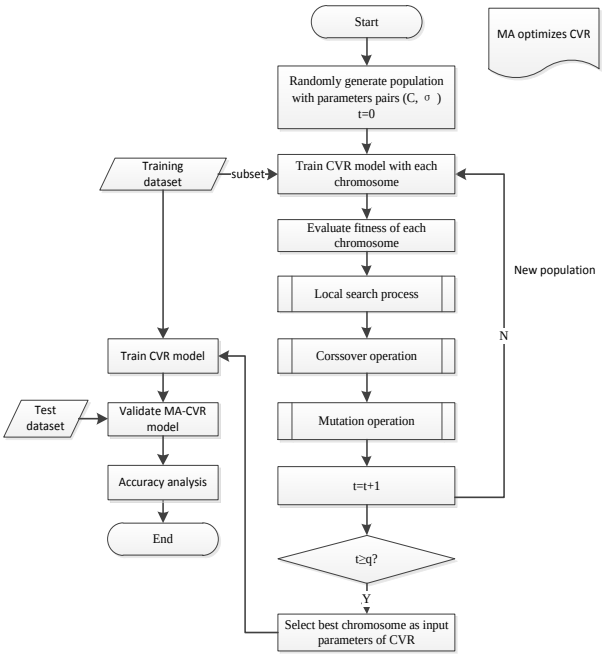

Figure 1. The Flowchart of MA-CVR

1. Initialization

Generate a population $P=\{X_1,...,X_n\}$ where $X_i(i=1,...,n)$ denotes the chromosome, n is the population size. Here we adopt real value encoding, C and σ^2 are coded in each chromosome directly with real value. For the chromosome $X_i=(x,y)$, x denotes the parameter C, and y denotes the parameter σ^2. The population size n should be selected carefully considering the trade-off between convergence and diversity.

2. Evaluation

Here we choose mean absolute percentage error (MAPE) as fitness function,

$$MAPE(X)=\frac{1}{l}\sum_{i=1}^{l}\left|\frac{a_i-p_i}{a_i}\right| \tag{2}$$

where l is the number of training dataset, a_i is actual value, p_i is the predicted value. The chromosome with smaller MAPE will have good fitness and have more chance to be selected into next generation.

According defined fitness function equation (2), we calculate each chromosome's fitness.

3. Local search

Local search is applied on each chromosome and determine whether it should be replaced with its neighbor with better fitness. Given a constant a, we calculate an increment by

$$d=a*rand() \tag{3}$$

where d is incremental value, $rand()$ is a random function. Then for each chromosome X_i, its local search procedure is displayed as Figure 2.

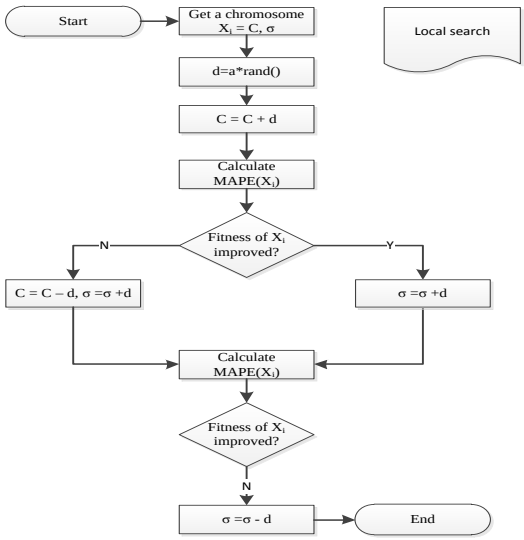

Figure 2. The Flowchart of Local Search

4. Crossover

The crossover operation is applied on randomly selected pair of chromosomes. Then local search is applied on the generated offspring. Given X_i, X_j the selected pair of parent, the real value crossover is expressed as below.

Move closer:

$$\begin{cases} X_i^{'} = X_i + \sigma\left(X_i - X_j\right) \\ X_j^{'} = X_j^{'} - \sigma\left(X_i - X_j\right) \end{cases} \tag{4}$$

Move away:

$$\begin{cases} X_i^{'} = X_i + \sigma\left(X_j - X_i\right) \\ X_j^{'} = X_j^{'} - \sigma\left(X_j - X_i\right) \end{cases} \tag{5}$$

where X_i, X_j represents the original pair selected. $X_i^{'}$ and $X_j^{'}$ represent the new generated offspring via crossover. And σ is random micro number which controls the variance of crossover operation.

5. Mutation

The first n chromosomes with best fitness are kept in population. And the mutation operation is applied on each chromosome. Given $C \in (C_u, C_l)$, $\sigma^2 \in (\sigma_u^{\ 2}, \sigma_l^{\ 2})$, C_u and C_l represent the upper bound and low bound of C respectively, $\sigma_u^{\ 2}$ and $\sigma_l^{\ 2}$ represent the upper bound and low bound of σ^2 respectively. After apply mutation on the chromosome $X_i = \{C_i, \sigma_i^{\ 2}\}$, the new generated individual $X_i^{'}$ is $X_i^{'} = \{C_i^{'}, \sigma_i^{\ 2}\}$ or $X_i^{'} = \{C_i, \sigma_i^{'\ 2}\}$. $C_i^{'}$ and $\sigma_i^{'}$ are expressed as below:

$$C_i^{'} = C_l + r\left(C_u - C_l\right) \tag{6}$$

$$\sigma_i^{'2} = \sigma_l^{\ 2} + r\left(\sigma_u^{\ 2} - \sigma_l^{\ 2}\right) \tag{7}$$

where r is a random number between 0 and 1.

6. Stopping criteria of MA

Repeat step 4-5 until the generation is equal to the specified maximum generation.

7. Train CVR model

The chromosome with best fitness in population will be selected as input parameters of CVR for training.

8. Prediction

The trained CVR model is used to predict and the results are analyzed.

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4. Case Studies

The load forecasting system based on MA-CVR model can be built as follows:
1. Collect and analyze historical information (load, temperature *etc*.)
2. Preprocess and normalize data
3. Identify training and test datasets
4. Define parameters of MA-CVR model
5. Validate model and analyze efficiency of model

4.1. Historical Data

The data used in this paper comes from EUNITE load forecasting competition in 2001 [11]. It contains the information of East-Slovakia Power Distribution Company from Jan 1997 to Jan 1999. The detail of the data is described in Table 1, and each number of the data is showed in the Count column:

Table 1. Data of East Elovakia Electric Corporation

Data Type	Time range	Count
Load half hourly	Jan 1, 1997~Jan 31, 1999	36, 528
Peak load daily	Jan 1, 1997~Jan 31, 1999	761
Average temperature daily	Jan 1, 1997~Jan 31, 1999	761
Annual holiday	1997~ 1999	45

4.2. Construction of Datasets And Samples

Table 2 defines the training set, validation set and testing set. Table 3 defines the sample construction.

Table 2. Training and Testing Dataset

Dataset	Time range	Count
Training set	Jan 1,1997~Oct 30, 1998	32016
Validation set	Nov 1, 1998~Dec 31, 1998	2881
Testing set	Jan 1, 1999~Jan 31, 1999	1441

Table 3. Sample Construction

Input	Variable	Description
1-5	l_1 historical load of same type day	Previous two hours' load half hourly
5-10	l_2 historical load of similar day	Same time of previous five same type day*
11	Average temperature	Average temperature of today

*We classified days into three categories: Tuesday, Wednesday and Thursday are the first category, Friday and Monday are the second category, and Saturday and Sunday are the last category. The days in same category are called same type day.

4.3. Model Parameters

In this paper, we compare MA-CVR to GA-CVR to optimize parameter C and σ of CVR. The mode parameters for MA-CVR and GA-CVR are defined as below in Table 4.

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Table 4. Training and Testing Dataset

Parameters	MA-CVR	GA-CVR
Population size	100/50/20	20
Max evaluation	3000	3000
Range of C	0.1~30000	0.1~30000
Range of σ	0~0.1	0~0.1
Selection strategy	Roulette wheel	Roulette wheel
Crossover strategy	Uniform	Uniform
Crossover probability	0.8	0.8
Mutation strategy	Gaussian	Gaussian
Mutation probability	0.01	0.01
CVR core function	Gaussian	Gaussian
Local search count	5/20/50	---

4.4 Evaluation Method

We use MAPE (Mean Absolute Percentage Error), MAX (Maximum Error) to evaluate the prediction result.

$$MAX = MAX(|a_i - p_i|) \tag{8}$$

where a_i denotes the real load, p_i denotes the prediction load

4.5 Results

4.5.1 Experiment 1: Compare different population size:

In this experiment, we use MA-CVR to optimize CVR's parameters with three different population sizes, 20, 50 and 100.

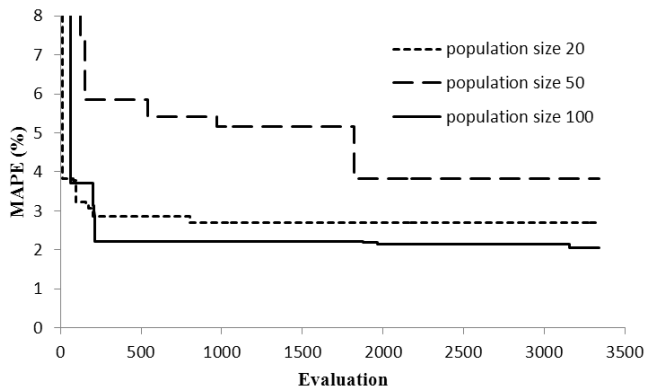

Figure 3. Optimization Process of MA With Population Size 20, 50 And 100

Figure 3 shows the optimization process of MA with different population size 20, 50 and 100. It can be seen from the Figure 3 that it takes about 800 evaluations to reach the best parameters for MA optimization process with population size of 20, about 1700 evaluations with 50 population size and about 3000 evaluations with 100 population size.

4.5.2 Experiment 2: Compare Different Local Search Count:

In this experiment, we use different local search count, which means how many individuals will be searched in the neighbor during local search process. We adopt 5, 20 and 5 separately.

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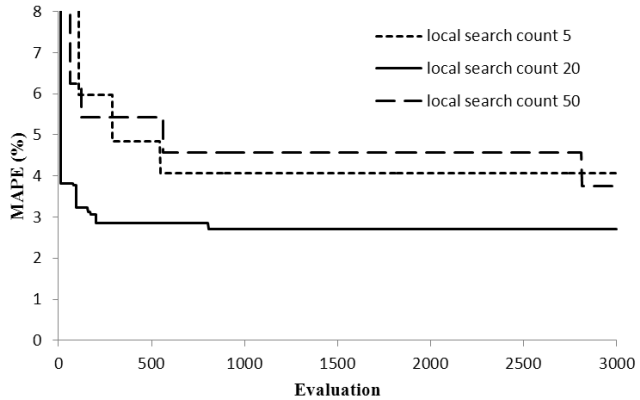

Figure 4. Optimization Process of Ma with Local Search Count 5 and 20

Figure 4 shows the optimization process of MA with different local search count 5, 20 and 50. From Figure 4, it takes about 600 evaluations to reach the best parameters for MA optimization process with 5 local search count, about 800 evaluations with 20 local search count and about 2700 evaluations with 50 local search count.

4.5.3 Experiment 3: Compare MA-CVR to GA-CVR:

In this experiment, we compare MA-CVR with GA-CVR during optimization process and prediction process.

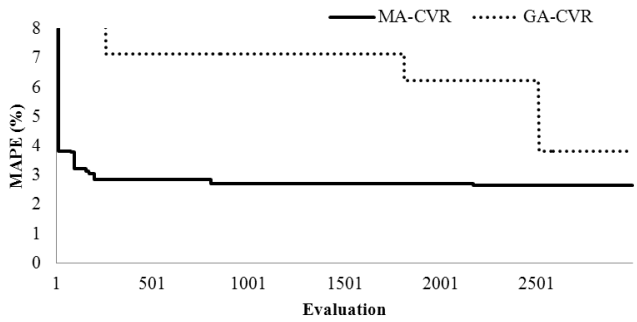

Figure 5. Optimization Process of MA-CVR and GA-CVR

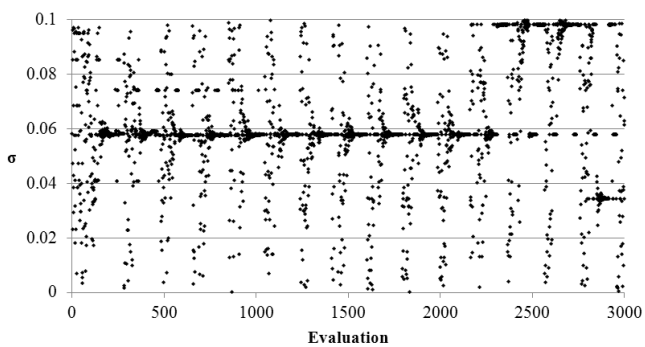

Figure 6. Parameter σ Distribution during MA Optimization Process

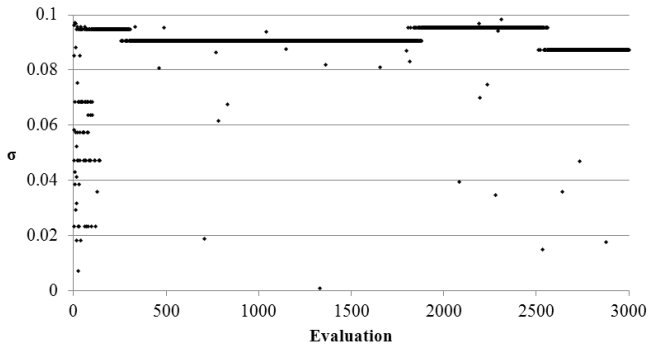

Figure 7. Parameter σ Distribution during GA Optimization Process

Figure 5 shows the optimization process of MA-CVR and GA-CVR. Figure 6 shows the parameter distribution during MA optimization process. Figure 7 shows the parameter distribution during GA optimization process. From Figure 5 we can see MA's optimization efficiency is better than GA. From Figure 6 and Figure 7, we can see MA can search more individuals in the neighbor of optimum which increase the chance to get better solution than GA and avoid falling into local optimum.

We use the optimization result to predict the first week's load of 1999. The prediction result is shown in Table 5.

Table 5. Prediction Result of MA-CVR and GA-CVR

Date	MA-CVR		GA-CVR	
	MAPE /%	MAX /MW	MAPE /%	MAX/MW
Jan 1,1999	1.55	29.33	1.43	28.50
Jan 2,1999	2.04	42.12	1.78	36.60
Jan 3,1999	2.15	41.56	2.01	45.72
Jan 4,1999	1.67	27.71	1.87	33.91
Jan 5,1999	1.91	40.25	1.99	43.42
Jan 6,1999	2.02	34.71	2.06	37.85
Jan 7,1999	1.67	30.71	1.92	35.72

From Table 5 we can see MA-CVR can get higher prediction accuracy than GA-CVR. For the seven days' prediction result, there are four days' MAPE which presents MA-CVR is better than GA-CVR and five days' MAX which shows that MA-CVR is better than GA-CVR.

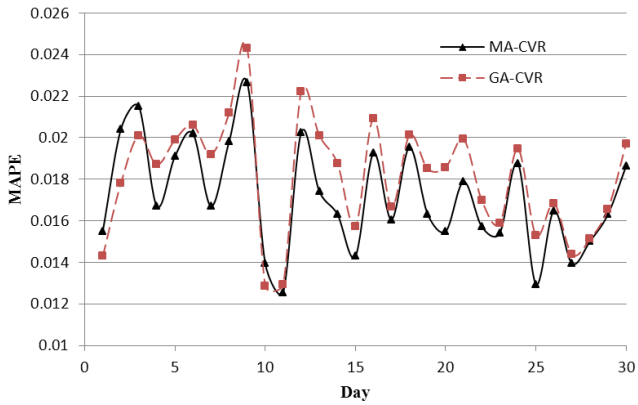

Figure 8. MAPE Results of MA-CVR and GA-CVR for A Month

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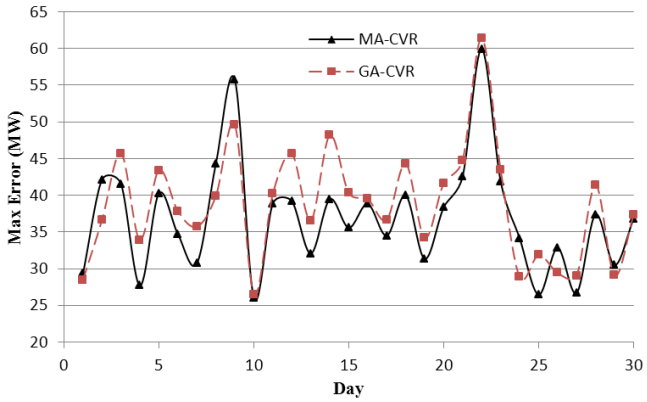

Figure 9. Max Error Results of MA-CVR and GA-CVR for a Month

The Figure 8 and Figure 9 show that the MAPE and MAX error prediction results of MA-CVR and GA-CVR for Jan 1999. The prediction accuracy of MA-CVR is better than GA-CVR's, showed in MAPE and MAX ERROR result.

4.5.4. Experiment 4: Compare MA-CVR with CVR and SVR:

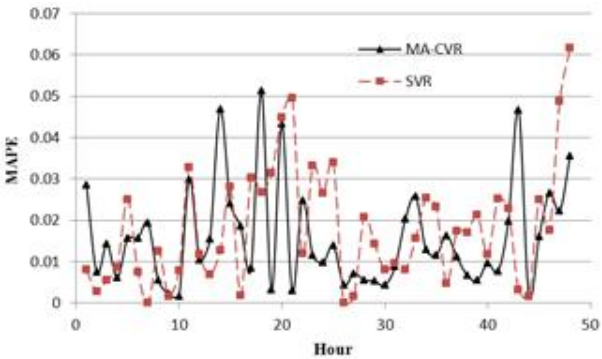

Figure 10. Prediction Results Of MA-CVR In Comparison With SVR For Jan.1 1999

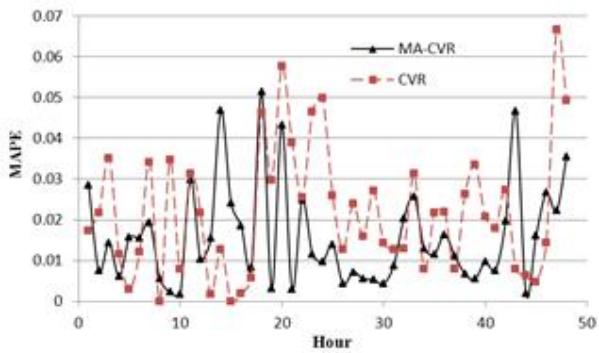

Figure 11. Prediction Results of MA-CVR In Comparison With CVR for Jan.1 1999

Figure 10 and Figure 11 show the comparison between MA-CVR of local search count 20 and population size 20 with other algorithms, the prediction results of which are quoted from the paper [24]. MA-CVR is better than SVR and CVR for Jan 1 1999.

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5. Conclusion

Through researching and analyzing MA and GA, we proposed a hybrid algorithm MA-CVR to solve the STLF problem. From the experiment results, we conclude that MA-CVR has following advantages compared with GA-CVR.

GA has a shortcoming that it is easy to fall into local optimum. MA can overcome this problem efficiently by adding a local search process in GA. MA-CVR can get optimum parameter of CVR faster than GA-CVR for the problem of STLF. During the same time period, MA-CVR can get better solution than GA-CVR with higher accuracy up to 0.31% in the experiments. MA-CVR can get higher prediction accuracy by taking optimization result into CVR, which is up to 0.65% in our experiment.

Also, we analyze the two impact factors which determine MA's optimization efficiency, population size and local search count. Larger population size will increase computation complexity and decrease optimization efficiency. And smaller local search count will make optimization easily fall into local optimum and decrease optimization efficiency.

Acknowledgements

This paper is supported by the Scientific Research Foundation for the Returned Overseas Chinese Scholars, State Education Ministry ([2013]693).

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