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# Load forecast method of electric vehicle charging station using SVR based on GA-PSO

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**Abstract.** This paper presents a Support Vector Regression (SVR) method for electric vehicle (EV) charging station load forecast based on genetic algorithm (GA) and particle swarm optimization (PSO). Fuzzy C-Means (FCM) clustering is used to establish similar day samples. GA is used for global parameter searching and PSO is used for a more accurately local searching. Load forecast is then regressed using SVR. The practical load data of an EV charging station were taken to illustrate the proposed method. The result indicates an obvious improvement in the forecasting accuracy compared with SVRs based on PSO and GA exclusively.

## 1 Introduction

With the development of the economy, exhaust emission from fuel vehicles has been one of the main factors of air pollution. At the same time, China's vehicle emission regulations are becoming more and more stringent. As a result, EVs are gradually favoured by people and supported by government. This brings large-scale demand for electricity, meanwhile, also results in negative influence on the load carrying capacity of power system.

At present, EV charging station load forecast methods are mainly classified into 3 categories. First, traditional load forecasting method includes regression, time series, wavelet analysis, grey model and neural network methods, etc[1,3,8,11,13]. However, due to lack of load data, it usually shows a large deviation in forecasting results. Second, the user behaviour modelling method based on statistical theory aims to analogy users' charging behaviour in order to forecast electric vehicle charging demand [2,7,14]. But the main problem with this method is that a deviation in behaviour analysis will cause a predictive systematic error. Third, SVM (support vector machine) prediction method can find the best balance between the empirical risk and the generalization risk, meanwhile, it can solve the small sample problem to achieve good results. Liu Wenxia et al [5] has made forecast on the EV charging load using SVM with GA (genetic algorithm), and good prediction results were obtained. Although GA can effectively solve the discrete optimization combination, and has strong global search ability, its local search ability is weak, which is difficult to get a more accurate optimal solution to the problem.

This paper presents a SVR method based on GA-PSO to forecast EV charging station load. In the whole process, FCM is used to select similar-day samples. GA is used to search global parameter in the first step and PSO for more accurately searching in the second step. Finally, the trained SVR is



regressed to forecast the load of an EV charging station. This method was applied in load forecasting of an EV charging station in Qingdao. The result shows an obvious improvement in the forecasting accuracy compared with using PSO and GA to optimize the parameters exclusively.

## 2 Sample similarity analysis

### 2.1 Extraction of sample influencing factors

Main influencing factors of EV charging station load are extracted and similarity selection is carried out, which can help to improve the efficiency of forecasting. Using correlation analysis, Liu Wenxia et al [5] found that the correlation between temperature and load was high. In addition, according to actual situation in China, the air quality index is also added in this paper. When the air quality is good, the traffic congestion degree increases, which leads to the increase of EV charging frequency. When the air quality is poor, the traffic congestion degree decreases, thereby decreasing the EV charging frequency. Here, 5 main factors affecting the extraction of similar samples, are maximum temperature, minimum temperature, weather conditions, date type and air quality.

Min-Max scaling method on temperature is carried out as follows:

$$y = \frac{x - x_{\min}}{x_{\max} - x_{\min}} . \quad (1)$$

Above,  $y$  is the normalized temperature;  $x$  is the maximum or minimum temperature of a day;  $x_{\max}$  and  $x_{\min}$  are the maximum and minimum values of the index inside the sample interval.

Min-Max scaling can standardize the data in the range of [0,1]. As of non-numeric variables, weather condition, date type and air quality need to be mapped to numerical values, shown in table 1.

Table 1: Weather conditions, date type and air quality

|                           | Variable                | Numerical Value |
|---------------------------|-------------------------|-----------------|
| <b>Weather conditions</b> | clear                   | 0               |
|                           | cloudy                  | 0.25            |
|                           | light rain / light snow | 0.5             |
|                           | Rain / snow             | 0.75            |
|                           | heavy rain / heavy snow | 0.1             |
| <b>Date type</b>          | working day             | 1               |
|                           | holiday                 | 0               |
| <b>Air conditions</b>     | excellent               | 0               |
|                           | good                    | 0.2             |
|                           | mild polluted           | 0.4             |
|                           | moderately polluted     | 0.6             |
|                           | severe polluted         | 0.8             |
|                           | serious polluted        | 1               |

### 2.2 Sample selection based on FCM

FCM [4,15] is applied to conduct similarity analysis on sample data, so as to improve the efficiency of sample training. Unlike k-means, data point is assigned membership to each cluster centroid as a result of which data point may belong to more than one cluster centroid.

Given data  $X = (x_{ij})_{n \times s}$  to be classified,  $i$  is the number of days in a given period of time;  $j$  is the number of characteristic variables for a single sample. FCM divides  $n$  samples into  $k$  ( $1 \leq k \leq n$ ) classifications, and  $V = [v_1, \dots, v_k]$  is the centroid of each cluster, where  $k=4$  is chosen in this paper. Let  $u_{ij}$  be a degree of membership of  $j$ th sample belonging to cluster  $i$ , where  $0 \leq u_{ij} \leq 1, \sum_{i=1}^k u_{ij} = 1$ . FCM algorithm requires each cluster centroid to meet:

$$\min J(U, V) = \sum_{j=1}^n \sum_{i=1}^k u_{ij}^p d_{ij}^2, \quad 0 \leq u_{ij} \leq 1, \sum_{i=1}^k u_{ij} = 1. \quad (2)$$

$U$  is a membership matrix and  $d_{ij} = \|x_j - v_i\|$  is the distance from the  $j$ th sample to cluster  $i$ . The threshold is set to 0.5. This means that samples with membership degree greater than 0.5 are viewed to be similar.

### 3 SVR forecasting method based on GA-PSO

#### 3.1 Support vector regression

Support Vector Machine [12] is based on VC Dimension theory and SRM (Structural Risk Minimization) principle. It seeks balance between model complexity and learning ability, in order to decrease actual error. In this paper,  $\varepsilon$ -SVR (support vector regression) method is selected for forecasting EV charging station load.

With  $\delta(x)$ ,  $\varepsilon$ -SVR converts the nonlinear prediction problem into a linear prediction problem in high dimensional space. This aims to convert the nonlinear prediction problem to a linear expression  $f(x) = \sum_{i=1}^m w_i K(x, x_i) + b$ . Solve the optimization problem under constraint conditions:

$$\begin{aligned} \min \quad & \frac{1}{2} \|w\|^2 + C \sum_{i=1}^k (\xi_i + \xi_i^*), \\ \left\{ \begin{array}{l} w^T \delta(x_i) + b - z_i \leq \varepsilon + \xi_i \\ z_i - w^T \delta(x_i) - b \leq \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \geq 0, i = 1, \dots, m \end{array} \right. \end{aligned} \quad (3)$$

The item  $\frac{1}{2} \|w\|^2$  in (3) is the distance between sample point and hyper-plane.  $C \sum_{i=1}^k (\xi_i + \xi_i^*)$  is a slack variable, which is mainly used for regularization. The dual optimization problem is as follows:

$$\begin{aligned} \min \quad & \frac{1}{2} (\alpha - \alpha^*)^T \delta(x_i)^T \delta(x_j) (\alpha - \alpha^*) + \varepsilon \sum_{i=1}^m (\alpha_i + \alpha_i^*) + \sum_{i=1}^m z_i (\alpha_i - \alpha_i^*), \\ \sum_{i=1}^m (\alpha_i - \alpha_i^*) = 0, \quad & 0 \leq \alpha_i, \alpha_i^* \leq C, i = 1, \dots, m. \end{aligned} \quad (4)$$

From (4),  $f(x) = \sum_{i=1}^m (-\alpha_i + \alpha_i^*) K(x_i, x_j) + b$  can be get, which is the predictive function and  $K(x_i, x_j)$  is the kernel function of  $\varepsilon$ -SVR.

Common kernel functions include polynomial function, linear function and radial basis function. For the choice of kernel function, there are no established standards. In this paper, RBF (radial basis function) kernel function is selected:

$$K(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right). \quad (5)$$

As of parameters of  $\varepsilon$ -SVR,  $C$  and  $\sigma$  have a great influence on the learning and generalization ability of the model. Therefore, this paper first uses GA for global parameter searching, then uses PSO for more accurate local optimal parameter searching, which will improve the accuracy of forecasting.

#### 3.2 GA and PSO

GA is one of evolutionary algorithmic models [9], which are designed to simulate genetic systems. In this algorithm, selection and crossover operator are the main driving operators. The goal of GA is to find the global optimal solution.

PSO [10] is a population-based search algorithm in the field of Computational Intelligence. It uses the concept of "swarm" and "particle". A PSO algorithm maintains a swarm of particles, where each particle represents a potential solution. During the process of searching optimal solution, all the

particles fly through a multidimensional search space, where the position of each particle is adjusted according to its own experience and that of its neighbours. The evolution equations of PSO are as follows:

$$v_{ij}(t+1) = wV * v_{ij}(t) + c_1 r_{1j}(t)(p_{ij}(t) - x_{ij}(t)) + c_2 r_{2j}(t)(p_{gj}(t) - x_{ij}(t)). \quad (6)$$

$$x_{ij}(t+1) = x_{ij}(t) + wP * v_{ij}(t+1) \quad (7)$$

Subscript  $j$  means  $j$ th dimension of particles;  $i$  means particle  $I$ ;  $t$  means swarm is updated to  $t$  generation;  $c_1$  and  $c_2$  are acceleration constants, where  $c_1$  regulates the step size of particles flying to the best position and  $c_2$  regulates the step size of particles flying to the global best position ( $c_1$  and  $c_2$  are valued at  $0 \sim 2$  in this paper);  $r_{1j} \sim U(0,1)$ ,  $r_{2j} \sim U(0,1)$  are randomly distributed parameters;  $wV$  and  $wP$  are the elastic coefficient in the process of velocity updating. In this paper, we set  $v_{\max} = k * x_{\max}$ ,  $0.1 \leq k \leq 1.0$  in order to reduce the possibility of particles leaving the search space during evolution.

### 3.3 Forecasting process of SVR based on GA-PSO

The whole forecasting process is as follows:

Step 1. EV station charging load data of 24-hour in a certain date range is selected.

Step 2. Use FCM to make classification to the sample data. Samples with degree of membership greater than 0.5 are selected as similar day sample set for training.

Step 3. In a given similar day sample set, select time 0 of the first day of that sample set to be the starting time. The inputs are the time 0 load of 4 days in that sample set, including the first day, and the output is the time 0 load of 5th day. According to this rule, the input and output quantities are extracted sequentially till reaching the final data in that sample set.

Step 4. Use GA to roughly search optimized parameters of  $C$  and  $\sigma$ .

Step 5. Use PSO to select the best parameters of  $C$  and  $\sigma$  based on the result from GA.

Step 6. Use the trained  $\epsilon$ -SVR to forecast EV station charging load at time 0.

Step 7. Judge whether the time point is 23. If “no”, return to step 3 to forecast load for the next time; if “yes”, end up the whole forecast process.

The flow chart is shown in figure 1 below:

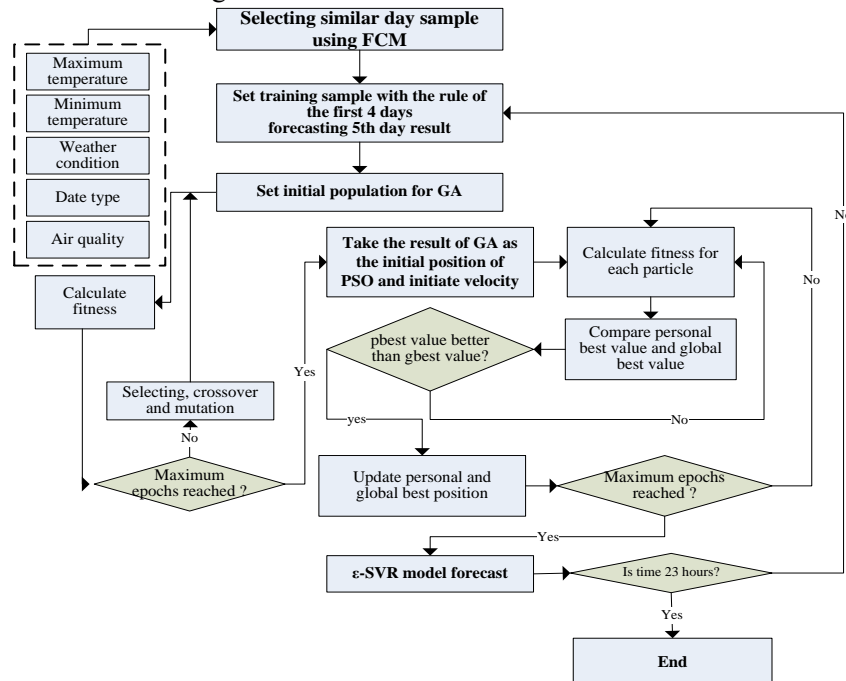


Fig 1: EV charging station load forecasting flow chart

#### 4 Empirical analysis

Empirical analysis of an EV charging station in Qingdao is made. A 24-hour charging load on July 1st, 2015 is forecasted, and data from April 1st to June 30th is taken as training data. SVRs based on PSO and GA exclusively are used to prediction for comparison.

Relative error  $E_R$  and root mean square error  $R_{MSRE}$  [6] are selected as evaluating indicators:

$$E_R = \frac{\hat{y}_i - y_i}{y_i} \quad (8)$$

$$R_{MSRE} = \sqrt{\frac{1}{n} \sum_{i=1}^n \left( \frac{\hat{y}_i - y_i}{y_i} \right)^2} \quad (9)$$

Results are shown in figure 2, figure 3 and table 2.

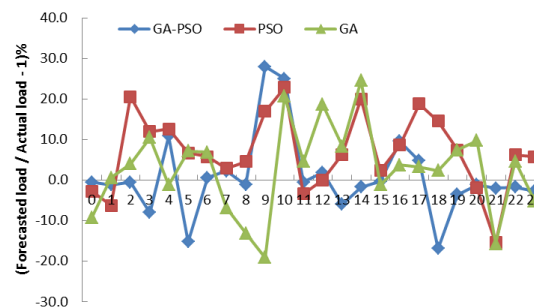


Fig 2 Relative error

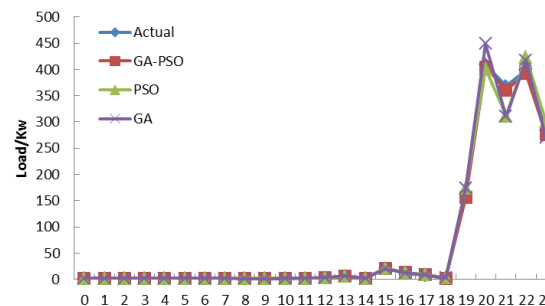


Fig 3 Forecasted and actual hourly load on July 1st, 2015

Table2: Comparison of load forecasting methods on 1st, 2015

| Time     | Actual Load | GA-PSO Forecasted Load | PSO Forecasted Load | GA Forecasted Load |
|----------|-------------|------------------------|---------------------|--------------------|
| 0:00:00  | 1.82        | 1.81                   | 1.77                | 1.65               |
| 1:00:00  | 1.75        | 1.73                   | 1.64                | 1.76               |
| 2:00:00  | 1.75        | 1.74                   | 2.11                | 1.82               |
| 3:00:00  | 2.00        | 1.84                   | 2.24                | 2.21               |
| 4:00:00  | 1.75        | 1.94                   | 1.97                | 1.73               |
| 5:00:00  | 2.1         | 1.78                   | 2.24                | 2.25               |
| 6:00:00  | 1.75        | 1.76                   | 1.85                | 1.87               |
| 7:00:00  | 1.75        | 1.79                   | 1.8                 | 1.63               |
| 8:00:00  | 1.75        | 1.73                   | 1.83                | 1.52               |
| 9:00:00  | 1.36        | 1.74                   | 1.59                | 1.10               |
| 10:00:00 | 1.40        | 1.75                   | 1.72                | 1.69               |

| Time       | Actual Load | GA-PSO Forecasted Load | PSO Forecasted Load | GA Forecasted Load |
|------------|-------------|------------------------|---------------------|--------------------|
| 11:00:00   | 1.75        | 1.74                   | 1.69                | 1.83               |
| 12:00:00   | 2.63        | 2.68                   | 2.63                | 3.12               |
| 13:00:00   | 5.85        | 5.5                    | 6.22                | 6.34               |
| 14:00:00   | 1.75        | 1.72                   | 2.1                 | 2.18               |
| 15:00:00   | 20.67       | 20.59                  | 21.15               | 20.43              |
| 16:00:00   | 11.59       | 12.7                   | 12.59               | 12.02              |
| 17:00:00   | 7.97        | 8.35                   | 9.47                | 8.23               |
| 18:00:00   | 2.55        | 2.12                   | 2.92                | 2.61               |
| 19:00:00   | 161.65      | 155.82                 | 173.59              | 173.64             |
| 20:00:00   | 409.15      | 404.38                 | 401.33              | 448.99             |
| 21:00:00   | 368.2       | 360.81                 | 311.33              | 310.28             |
| 22:00:00   | 398.9       | 391.92                 | 423.71              | 417.44             |
| 23:00:00   | 283.85      | 275.99                 | 300.11              | 269.25             |
| $R_{MSRE}$ | --          | <b>9.79%</b>           | <b>11.46%</b>       | <b>10.89%</b>      |

It can be concluded that using SVR based on GA-PSO method has the minimum errors  $R_{MSRE}$  of 9.79%, while  $R_{MSRE}$  using SVR based on PSO is 11.46% and GA, 10.89%. In addition, there are 15 time points' forecasted load errors among 24 points using SVR based on GA-PSO that are smaller than those of the other two methods. Among all the errors from SVR based on GA-PSO, 14 errors are within the range of  $\pm 3\%$ . Therefore, SVR based on GA-PSO improves the accuracy of load forecasting.

## 5 Conclusions

(1) The FCM method is used to extract similar sample set, which increases the correlation of the data. SVR method is used for modelling, which has global optimization and better generalization performance. Empirical analysis results show that the daily load forecasting error of an EV charging station is 9.79%, which can basically meet the requirements of EV charging station's daily control.

(2) Compared with the SVR model based on PSO and GA exclusively, SVR based on GA-PSO improves the accuracy of load forecasting by 1.67% and 1.1% respectively.

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