Charging Load Forecasting of Electric Vehicle Charging Station Based on Support Vector Regression

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***Abstract*—In allusion to the problem that electric vehicle(EV) charging time and state of charge(SOC) randomness leads to the traditional application of EV charging load characteristic forecasting method low accuracy problem, applying support vector regression(SVR), a charging load forecasting model based on historical load is proposed. The proposed model considers various kinds of factors which could influence the load, including the historical data of charging load, the number of EVs, the number of normal working charging pile, weather information, week properties, holiday properties and other information, in addition, the model corrects the false data before the establishment of the training sample set, which effectively improves the precision of forecasting. The effectiveness and correctness are validated by numerical example of an EV charging and switching station.**

***Index Terms*-- electric vehicle, support vector regression(SVR), charging load forecasting, state of charge (SOC).**

I. Introduction

With the growing concern on energy and environmental crisis, electric vehicles (EVs) are spreading all over the world rapidly. However, the charging load of large-scale EVs is high, fluctuant and uncertain, which will bring negative effects on power grid, such as increased peak load, voltage fluctuations [1]-[9]. To reduce the negative effects caused by EVs, the charging load forecasting model needs to be proposed. There are two main types of charging load forecasting method currently:

A. Based on the Driving Characteristics of Electric Vehicles

Under hypothesis that travel time and state of charge (SOC) obey a certain distribution, method herein gets start charging time of electric vehicles and SOC by sampling and figures out charging load value at all times combining charging and discharging characteristics of electric vehicles. BP neural network is applied to forecast charging load with residential area and population density as input layer in [10]. In [11] the numerical method of electric vehicle charging load is formulated to analyze the effect of electric vehicle charging load on distributing network. Ref [12] uses board GPS to collect information on SOC, leaving time, arriving time and parking place to forecast charging load by applying deterministic and stochastic methods. Starting with factors affecting charging station loads, the method is simple but has larger deviation for the randomness of driving characteristics of electric vehicles.

B. Based on Random Process of Electric Vehicles Arriving at Charging Station

In this method, number of electric vehicles arriving at charging stations and charging requirements are assumed to obey certain random process. Ref [13] concludes that the probability distributions of number of electric vehicles arriving at charging stations at certain time by Queuing Theory and analyzes remaining capacity and charging requirement of each electric vehicle by probability distributions of running distance, which are combined to get the distribution of charging power sequence in charging station. In this way, randomness of starting time of electric vehicle charging and remaining capacity can be calculated and play an important role in planning and construction of charging station. However, the model is complex and difficult to calculate and needs further study.

In order to forecast charging load of electric vehicles better, this paper considers comprehensively all factors affecting conventional loads in charging stations of electric vehicles, the model of which based on historical information and support vector regression (SVR) will improve greatly the accuracy of forecasting on loads in charging stations of electric vehicles.

II. Support Vector Regression Theory

When the linearity of sample is separable, the mathematical model of support vector machine (SVM) can be expressed by (1).

$$\begin{aligned} &\min \frac{1}{2}\|w\|^2 \\ &s.t.\ y_i[(w\cdot x_i)+b]-1\geq 0, i=1,\ldots N \end{aligned} \tag{1}$$

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w means the slope of linear discriminant function; b means its intercept; (x_i, y_i), $i = 1,...N$ is the training sample.

The constraint condition of the above mathematical model is to classify all training samples correctly, however, it's always hard to meet the constraint condition in practice. So slack variable ξ needs to be introduced, which allows incorrect classification of few samples when the classification should meet (2).

$$y_i[(w \cdot x_i) + b] \geq 1\text{-}\xi_i, \quad i = 1,...N \tag{2}$$

The introduction of slack variable comparatively relaxes the constraint condition, which improves the fault-tolerant capability of SVM and popularizes its application fields meanwhile. It can be observed from (2) that, to reduce the incorrect sample classifications, the value of slack variable corresponding to all sample points in the model should be made to reach minimum. For this purpose, penalty term $C\sum_{i=1}^{N}\xi_i$ can be added on the basis of objective function $\frac{1}{2}\|w\|^2$. And the new mathematical model of SVM turns into (3).

$$\begin{aligned} &\min \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N}\xi_i \\ &s.t.\ \ y_i[(w \cdot x_i) + b] \geq 1 - \xi_i, i = 1,...N \\ &\qquad \xi_i \geq 0, i = 1,...N \end{aligned} \tag{3}$$

After introducing the slack variable, the SVM's generalization ability improves significantly. But this method can be only used under separable linearity of sample data. However, many sample data is inseparable practically. For this reason, a certain proper nonlinear mapping $x \to \phi(x)$ can be brought in, the problem of linear separability in original space can be changed into the problem of linear separability in higher space. Therefore, when the linearity of sample is inseparable, the model is going to further change as (4).

$$\begin{aligned} &\min \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N}\xi_i \\ &s.t.\ \ y_i[(w \cdot \phi(x_i)) + b] \geq 1 - \xi_i, i = 1,...N \\ &\qquad \xi_i \geq 0, i = 1,...N \end{aligned} \tag{4}$$

Lagrange function is constituted according to (4).

$$L(w,b,\alpha,\xi) = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N}\xi_i - \sum_{i=1}^{N}\alpha_i(y_i(w\cdot\phi(x_i)) + b - 1 + \xi_i) - \sum_{i=1}^{N}\beta_i\xi_i \tag{5}$$

$\alpha = (\alpha_{1,...}\alpha_N), \alpha_i \geq 0$ and $\beta = (\beta_{1,...}\beta_N), \beta_i \geq 0$ are Lagrange parameter.

Under KKT condition, partial differential of (5) to w, b, we can get $\phi(x)$.

$$\begin{aligned} w &= \sum_{i=1}^{N}\alpha_i y_i \phi(x_i) \\ b &= y_j - \sum_{i=1}^{N}\alpha_i y_i (\phi(x_i)\cdot\phi(x_j)) \end{aligned} \tag{6}$$

Substituting the result of (6) into (3), then we can get the simplified model:

$$\begin{aligned} &\max \sum_{i=1}^{N}\alpha_i - \frac{1}{2}\sum_{i=1}^{N}\sum_{i=1}^{N} y_i y_j \alpha_i \alpha_j (\phi(x_i)\cdot\phi(x_j)) \\ &s.t. \sum_{i=1}^{N} y_i\alpha_i = 0, i = 1,...N \\ &\qquad \alpha_i \in [0,1], i = 1,...N \end{aligned} \tag{7}$$

By comparing (7) with (3), it is shown that nonlinear mapping $\phi(x)$ in (3) appears alone; however in (7), it appears in the form of inner product $(\phi(x_i)\cdot\phi(x_j))$, which means, the decision function can be acquired by figuring out inner product $(\phi(x_i)\cdot\phi(x_j))$ of $\phi(x)$ without knowing specific form of $\phi(x)$.

The training of training sample set is conducted via (7) to get $\alpha^* = (\alpha_1^*, ...\alpha_N^*)$ under optimality condition, then substituting it into (6) to acquire w^*、b^* under optimality condition, finally we can get SVR function:

$$f(x) = \sum_{i=1}^{N}\alpha_i^* y_i(\phi(x)\cdot\phi(x_i)) + y_j - \sum_{i=1}^{N}\alpha_i^* y_i(\phi(x_i)\cdot\phi(x_j)) \tag{8}$$

III. Conventional Charging Load Forecasting Model Based on Support Vector Regression

A. Determining Input of SVR Model

1) Characteristics and Influencing Factors of Conventional Charging Load

a) In order to present the cyclicity of conventional charging loads, loads of the same time in first seven days are chosen as $L = \{L_1, L_2, L_3, L_4, L_5, L_6, L_7\}$.

b) Week property of the forecasting day is $W \in \{1,2,3,4,5,6,7\}$.

c) Festival property of the forecasting day is $F \in \{0,1\}$. *If it is on holiday, then* $F = 1$, *otherwise F=0.*

d) Weather condition of the forecasting day is $A \in \{1,2,3\}$ (if it is sunny, then A=1, if it is cloudy, then A=2, if it is rainy or snowy, then A=3).

e) Temperature of the forecasting day is T.

f) Number of vehicles on plan of forecasting day is B.

g) Number of charging piles available on predivting day is C.

Taking the seven parts above, the input vector of support vector regression and forecasting sample set is a 13 D input vector $\{L_1, L_2, L_3, L_4, L_5, L_6, L_7, W, F, A, T, B, C\}$.

2) Pretreatment of Sample Imput

Malfunction of data acquisition communication system in electric vehicle charging station may causes some negative power charger and gap between historical data in charging station database and true historical data, that is to say, there are "defective pixels" (not real data) in historical data. To prevent these "defective pixels" from impacting on the accuracy of forecasting result, this study corrects "defective pixels". Since charging loads are periodic, this paper uses average value of the same time in two successive days as the corrected value of "defective pixels".

On the other hand, since magnitude and variation range of sample data are different from each other, this paper normalizes training sample set and forecast sample set to prevent covering among data of different variation range and overflow in calculation.

B. Selecting Kernel Function of SVR Model

After introducing kernel function, SVR can get the final solution by figuring out inner product $(\phi(x_i)\cdot\phi(x_j))$ of $\phi(x)$ without knowing specific form of $\phi(x)$. According to the principle of Hilbert-Schmidt, a kernel function must be a symmetrical function satisfying theorem of Mercer. Linear Kernel, Polynomial Kernel and Radial Basis Function (RBF) are most commonly used.

SVR prediction model depends on the kernel function and arguments selected to a great extent. By rational arguments selecting, it can be applied to any sample distribution. Overall model performance trained by RBF is better than those by other kernel functions when dealing with high-dimensional large sample [14]. The input dimension of this paper(13D) and the number of training samples are large. Considering the good performance of RBF on high-dimensional large sample, RBF is selected in present invention to establish SVR model:

$$K(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|}{\delta^2}\right) \tag{9}$$

C. Selecting Arguments of SVR Model

Penalty factor C has great influence on learning and generalization ability of Support Vector Regression and determining arguments is a key research issue in Support Vector Regression Theory. Generally speaking, the value of penalty factor C is related to learning sample and practical issue and will affect the structural risks and sample error. When C is too small, the penalty of sample data is also small, which causes larger training error. When C is too large, learning accuracy is high but generalization ability of model is lower [15]. Furthermore, the value of penalty factor C has influence on management of outliers in samples. Therefore, a proper value is anti-interference and able to maintain accuracy and stability of regression model.

D. Conventional Charging Load Forecasting Process Based on SVR

After the establishment of SVR model, historical information of all 150 days before forecasting is trained as sample to gain SVR forecasting model to predict conventional charging load of charging station. The concrete develop process is as follows:

1) Collect conventional charging load of charging station of all 150 days before forecasting day and historical data that will have influence on the load, including week property, festival property, temperature, weather condition, number of vehicles served by charging station and chargers available.

2) Scan historical data of conventional charging load of charging station. If there is negative one, then average value of the same time of the day before and after is used as corrected charging load.

3) Dertermine value of each factor affecting conventional charging load of charging station. Temperature and weather condition is determined by weather forecast and number of vehicles served by charging station and chargers available are determined by data provided by charging station.

4) Normalize values of historical charging load, week property, festival property, temperature, weather condition, number of vehicles served by charging station and chargers available.

5) Build training sample set and sorecast sample set with historical data at k'o clock on forecast day.

6) Gain lagrange multiplier of corresponding SVM at k'o clock using training sample set and build SVR forecast model corresponding with k'o clock.

7) Use forecast sample set in SVM forecast model to get forecast value of conventional charging load of charging station corresponding with k'o clock.

8) Repete Step 5) to 7) to get forecast value of conventional charging load of charging station of all moment in forecasting day.

9) After forecasting, present forecast value of conventional charging load of charging station of all moment in forecasting day in form of curve by applying graphical display tool and save all forecasting value in database.

IV. PRACTICAL EXAMPLES AND ANALYSIS

JZ electric vehicle charging station in Shandong is applied in this paper as practical example to forecast its charging load. Historical data of conventional charging load of charging station of all 150 days before forecasting day (charging load, week property, festival property, temperature, weather condition, number of vehicles served by charging station and chargers available) are input samples in which “defective pixels” will be corrected and normalized to get training sample set. Lagrange multiplier of corresponding SVM at each moment from training sample set is used to build SVR forecast model corresponding with certain moment. Then use forecast sample set in SVR forecast model to get forecast value of conventional charging load of charging station of certain moment, which is repeated to get all value of forecasting day.

A. Forecast Curve of Conventional Charging Load

Charging load of electric vehicles charging station forecasted by SVR based on historical load is shown in blue curve of Fig. 1. In order to compare method mentioned in this paper and traditional method and show promotion in forecasting accuracy, black curve in Fig. 1 shows conventional charging load forecasting result of traditional method based on running characters of vehicles. The red curve shows practical charging load of electric vehicle charging station on forecasting day.

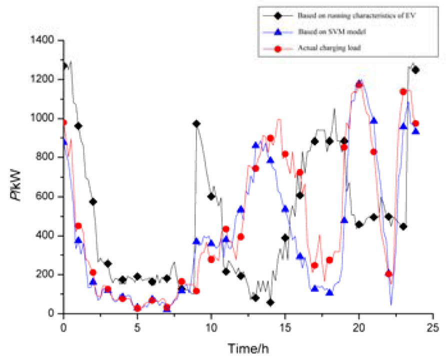

Figure 1. Conparison between SVR Forecasting Model and Traditional Forecasting Model

Fig. 1 shows that curves of forecasting charging load based on SVR forecasting model and actual charging load are similar in trend and forecast values are close to actual values. Electric vehicles began to charge after 18’o clock and conventional charging load of charging station went higher gradually and reached highest (1200kW) around 20’o clock. The blue curve shows that forecast based on SVR also reaches peek around 20’o clock with 1171 kW. After 20’o clock, SOC of some electric vehicles reached 90% gradually and charging power of those vehicles went down which finally exited when fully charged. Since the number of electric vehicles was large, when the first batch of vehicles were fully charged, the second batch of vehicles began to charge. Therefore, there would be another peek between 23 to 24’o clock, the predicted value and actual value were 1085 kW and 1143 kW respectively. What’s more, running mileage of electric vehicles in one day is long while the endurance power of charges are not good enough, so between 12 to 16’o clock in day time the conventional charging load in charging station is also high. However, traditional forecasting curve based on running characteristics of electric vehicles and actual charging power curve differ in the time of peek and trend. There is gap between predicted value and actual value so it can not reflect characteristics of conventional charging load. Therefore, compared with traditional forecasting method based on running characteristics of electric vehicles, SVM forecasting model based on historical data can improve accuracy of conventional charging load forecasting efficiently.

B. Accuracy of Conventional Charging Load Forecasting Based on SVM

In order to show advantages of forecasting method of conventional charging load of electric vehicle charging station in this paper directly, Mean absolute error and root-mean-square error are chosen to assess the two forecasting methods (see in Tab. Ⅰ). Computational formula of mean absolute error and root-mean-square error is:

$$MAE=\frac{\sum_{i=1}^{n}\left|y_i^p-y_i\right|}{n} \tag{9}$$

MAE is the predicted mean absolute error; n is amount of forecasting plots; y_i^p is the forecasting value of point i; y_i is the actual value of point i.

$$RMSE=\sqrt{\frac{\sum_{i=1}^{n}(y_i^p-y_i)^2}{n}} \tag{10}$$

$RMSE$ is the predicted root-mean-square error.

TABLE I. FORECASTING CHARGING LOAD BASED ON SVM MODEL

	Based on Running Characteristics of Electric Vehicles	**Based on SVM Model**
Mean Absolute Error (MAE/kW)	345.571	103.836
Root-Mean-Square Error (RMSE/kW)	406.801	149.860

Tab. Ⅰ shows that mean absolute error of forecasting charging load based on running characteristics of electric vehicles is 345.571kW, and root-mean-square is 406.801kW; Mean absolute error of forecasting charging load based on historical load in SVM model is lowered to 103.836kW and root-mean-square is lowered to 149.860kW. The mean absolute error in latter is lowered by 69.95% and root-mean-square error is lowered by 63.16%. There is significant improvement in both indicators. Therefore, SVM forecasting model mentioned in this paper based on historical data can improve accuracy of conventional charging load forecasting of electric vehicle charging station efficiently.

V. CONCLUSION

In this paper, as the predication error is large due to electric vehicles' driving randomness when traditional electric vehicles' driving characteristic method is adopted to predict the battery charging load, it studies a support vector regression model based on history load to predict normal charging load. In this model, SVR method is adopted, and various kinds of factors that influence the normal charging load of electric vehicle charging station are considered comprehensively, including the history load of normal charging, quantity of electric vehicles, number of normal working charging pile, weather condition, week property, festival property, etc. Besides, before establishing training sample set, "defective pixels" (not real data) in history data are also corrected by this model, which improves the precision of model prediction effectively.

According to the proposed charging load forecasting model in this paper, JZ electric vehicle charging station in Shandong is analyzed and researched. The results show that the mean absolute error and root-mean-square error reduced by 69.95% and 64.56% compared with traditional charging load forecasting under driving characteristics of electric vehicles. The result verifies the correctness and effectiveness of SVR model based on the history load.

REFERENCES

[1] Ma ZJ, Callaway D, and Hiskens I, "Decentralized charging control for large populations of plug-in electric vehicles: Application of the Nash certainty equivalence principle," *Proceedings of IEEE Conference on Decision and Control*, pp. 191–195, 2010.

[2] Clement K, Haesen E, and Driesen J, "The impact of charging plug-in hybrid electric vehicles on a residential distribution grid," *IEEE Transactions on Power Systems*, vol. 25(1), pp. 371-380, 2010.

[3] Staats PT, Grady WM, Arapostathis A, et al, "A statistical method for predicting the net harmonic currents generated by a concentration of electric vehicle battery chargers, " *IEEE Transactions on power Delivery*, vol. 12(3), pp. 1255-1266, 1997.

[4] He YF, Venkatesh B, and Guan L, "Optimal Scheduling for Charging and Discharging of Electric Vehicles," *IEEE Transactions on Smart Grid*, vol. 3(3), pp. 1095-1105, 2012.

[5] Fernández LP, Román T, Cossent R, et al, "Assessment of the impact of plug-in electric vehicles on distribution networks, " *IEEE Transactions on Power Systems*, vol. 26(1), pp. 206-213, 2011.

[6] Blumsack S, Samaras C, and Hines P, "Long-term electric system investments to support plug-in hybrid electric vehicles, " *Proceedings of IEEE Power and Energy Society General Meeting*, 2008.

[7] Dyke KJ, Schofield N, and Barnes M, "The impact of transport electrification on electrical networks," *IEEE Transactions on Industrial Electronics*, vol. 57(12), pp. 3917-3926, 2010.

[8] Taylor J, Maitra A, Alexander M, et al, "Evaluation of the impact of plug-in electric vehicle loading on distribution system operations, " *Proceedings of IEEE Power and Energy Society General Meeting*, 2009.

[9] Kelly L, Rowe A, and Wild P, "Analyzing the impacts of plug-in electric vehicles on distribution networks in British Columbia, " *Proceedings of IEEE Electric Power Energy Conference*, 2009.

[10] Madrid C, Argueta J, and Smith J, "Performance characterization-1999 Nissan Altra-EV with lithium-ion battery," California, Southern California EDISON, 1999.

[11] Qian KJ, Zhou CK, and Malcolm, "A modeling of load demand due to EV battery charging in distribution systems," *IEEE Transactions on Power Systems*, vol. 26(2), pp. 802-810, 2011.

[12] Ashtari A, Bibeau E, Shahidinejad S, et al, "PEV charging profile prediction and analysis based on vehicle usage data," *IEEE Transactions on Smart Grid*, vol. 3(1), pp. 341-350, 2012.

[13] Li G ，Zhang XP, "Modeling of plug-in hybrid electric vehicle charging demand in probabilistic power flow calculations," *IEEE Transactions on Smart Grid*, vol. 3(1), pp. 492-499, 2012.

[14] Amari S, Wu S, "Improving support vector machine classifiers by modifying kernel functions," *Neural Networks*, vol. 12(6), pp. 783-789, 1999.

[15] Qiao H，Zhou LH，Pan WH, et al, " Based on the parameter adaptive power plant thermal parameter soft measurement of SVR," *Journal of north China electric power university*, vol. 35(2), pp. 94-97，2008．