http://dx.doi.org/10.5755/j01.eee.19.6.4554 ELEKTRONIKA IR ELEKTROTECHNIKA, ISSN 1392-1215, VOL. 19, NO. 6, 2013

Prospective Analysis of Distribution Network Reconstruction on Electric Vehicles access to Demonstration District

Liu Yujun[1], Xu Qingshan[1], Chen Kai[2], Xu Xiaohui[3]
[1]*School of Electrical Engineering, Southeast University, Sipailou 2#, Nanjing, Jiangsu, China, 210096*
[2]*Nanjing Power Supply Company, JiangSu Electric Power Company, Shanghai Road 215#, Nanjing, China, 210000*
[3]*China Electric Power Research Institute, Nari Road 8#, Nanjing, Jiangsu, China, 210061*
xuqingshan@seu.edu.cn

***Abstract*—With the accelerated pace of plug-in electric vehicles (EV) access to the smart grid, large quantities of EV charged in old communities may cause the overload of distribution network. Reconstruction of the network appropriately and accordingly should be a fundamental solution to prevent the potential crisis. In this paper, prospective scale of EV is firstly estimated with the statistics of historical ownership of vehicles through logistic curve based on least absolute deviation (LAD) method. Under the scenarios estimated, the Monte Carlo simulation method is applied to determine the starting state of charge (SOC) and the initial point. Then an assumed demonstration district is employed to study the charging load in the uncoordinated charging mode at different EV penetration level. Simulation results indicate that, in the future, EV will pose great pressure on the distribution network and the reconstruction of power facilities such as transformers and transmission lines is necessary to ensure the security and stability of the network.**

***Index Terms*—Demonstration district, Distribution network reconstruction, Electric vehicles, Monte Carlo simulation, Least absolute deviation, Logistic curve model, Prospective analysis.**

I. INTRODUCTION

With the improvement of living conditions, the demand for oil is rapidly growing. Researchers all over the world are hardly working on the application of renewable energy [1, 2]. In the fact, the transportation sector is responsible for over half of world oil consumption. Because of the shortage of oil, the vehicles which use renewable energy as fuel are developing faster than other sectors especially for electric vehicles (EV). But EV also brings the problem of charging load and heavy circuit. It is necessary to forecast the growth trends and level correctly to help build the distribution network.

Manuscript received January 14, 2013; accepted April 4, 2013.
This research was funded by National High Technology Research and Development Program of China (863 Program) (No. 2012AA050214), Natural Science Foundation of Jiangsu Province (No. BK2012753), the Fundamental Research Funds for the Central Universities (No. 3216002103), and National Energy Administration(NY20110702-1).

There are many kinds of methods to estimate the vehicles ownership. Because the Logistic curve is suitable for the regular pattern of vehicles ownership development, we use least absolute deviation (LAD) to fit it. Reference [3] gave some suggestions on curve fitting with LAD method by linear programming. Reference [4] mainly researched on the errors between LAD and Least Square method. Reference [5] improved the robustness of LAD regression through a judicious choice of weights. Furthermore, it also provided an efficient algorithm to solve the general nonlinear, mixed integer programming problem when the number of predictors is small.

There are also many researches on vehicles ownership estimation. Reference [6], [7] made the forecast based on different conjoint analysis methods. What's more, reference [8]–[10] analysed the impact on EV access to the distribution network. This paper researches on the estimation of vehicles ownership in the future based on LAD method. And then a demonstration district is built to analyse EV's impact on the distribution network and the way to reconstruction it without causing the crisis.

II. LEAST ABSOLUTE DEVIATION METHOD

A. Development

Least Absolute Deviation method (LAD) is firstly proposed by mathematicians Boscovitch and Laplace during 1755—1757 when they were studying on the linear fitting. Because of its difficulty to calculate, LAD method was developing very slowly. And in this paper, we choose to use a new solution to LAD method [11].

LAD method is one kind of curve fitting method which makes absolute deviation as criterion to choose parameters. The formula can be defined as

$$\sum_{i=1}^{m}\left|y_i - f\left(x_i, \boldsymbol{a}\right)\right| = \min. \qquad (1)$$

For regression problems where there may be outliers in the dependent variable, LAD regression is a good alternative to Least Squares (LS) [12]. While LAD is intuitive and ideal but it is its absolute value that makes it difficult to calculate. In order to exclude the influence of the absolute value, we must have this theorem.

B. Theorem

Assume that there exists $\boldsymbol{a}=\boldsymbol{a}^{*}\in R_n$ which makes

$$Q=Q\left(\boldsymbol{a}^{*}\right)=\sum_{i=1}^{m}\left|y_i-f\left(x_i,\boldsymbol{a}^{*}\right)\right|=\min \tag{2}$$

established. Then the fitting curve $f\left(x,\boldsymbol{a}^{*}\right)$ can be expressed as follows: if there are at least n points which are suitable for

$$y_i-f\left(x_i,\boldsymbol{a}^{*}\right)=0 \quad i=1,2,\cdots,n, \tag{3}$$

then we call the n points Point Zero. Otherwise the minimum of the curve is not existed.

C. Solution

We cannot achieve the best $\boldsymbol{a}^{*}$ through the directly analytical method. So a small deviation $\Delta\boldsymbol{a}$ is attached to $\boldsymbol{a}^{*}$ and $\boldsymbol{a}^{*}=\boldsymbol{a}+\Delta\boldsymbol{a}$ is defined. When $\Delta\boldsymbol{a}$ is small enough, we can have $\left\|y-f\left(x,\boldsymbol{a}^{*}\right)\right\|_1=\min_{\boldsymbol{a}+\Delta\boldsymbol{a}\in\boldsymbol{R}_n}\left\|y-f\left(x,\boldsymbol{a}+\Delta\boldsymbol{a}\right)\right\|_1\approx$ $\approx\min_{\boldsymbol{a}+\Delta\boldsymbol{a}\in\boldsymbol{R}_n}\left\|y-f\left(x,\boldsymbol{a}\right)-\frac{\partial f\left(x,\boldsymbol{a}\right)}{\partial\boldsymbol{a}}\Delta\boldsymbol{a}\right\|_1$.

In this way we can get the approximate solution. To get the extreme values of (2), the necessary condition $\frac{\partial Q}{\partial a_1}=0$, $\frac{\partial Q}{\partial a_2}=0$, $\cdots$, $\frac{\partial Q}{\partial a_n}=0$ is applied:

$$\begin{cases}\sum_{i=1}^{m}\frac{r_i}{\left|r_i\right|}\bullet\frac{\partial f}{\partial a_1}=0,\\ \sum_{i=1}^{m}\frac{r_i}{\left|r_i\right|}\bullet\frac{\partial f}{\partial a_2}=0, \qquad r_i\neq 0,\\ \vdots\\ \sum_{i=1}^{m}\frac{r_i}{\left|r_i\right|}\bullet\frac{\partial f}{\partial a_n}=0,\end{cases} \tag{4}$$

where $r_i=y_i-f\left(x_i\right)$, $\frac{\partial f}{\partial a_j}=\frac{\partial f\left(x,\boldsymbol{a}\right)}{\partial a_j}$, $j=1,2,\cdots,n$.

For the sake of simplicity, we define $\sum=\sum_{i=1}^{m}$, $\varphi_j=\varphi_{i,j}$ and use k as the iteration number. Substitute the first order Taylor expansion of $f\left(x,\boldsymbol{a}\right)$ at $\boldsymbol{a}^{(0)}$ into (4):

Use the first order Taylor expansion of $f\left(x,\boldsymbol{a}\right)$ at $\boldsymbol{a}^{(0)}=\left(a_1^{(0)},a_2^{(0)},\cdots,a_n^{(0)}\right)^{\mathrm{T}}$

$$\begin{aligned}f\left(x,\boldsymbol{a}\right)&=f\left(x,\boldsymbol{a}^{(0)}\right)+\varphi_1\Delta a_1+\varphi_2\Delta a_2+\cdots+\varphi_n\Delta a_n=\\&=f\left(x,\boldsymbol{a}^{(0)}\right)+\sum_{j=1}^{n}\varphi_j\Delta a_j,\end{aligned} \tag{5}$$

where $\varphi_j=\left.\frac{\partial f\left(x,\boldsymbol{a}\right)}{\partial a_j}\right|_{\boldsymbol{a}=\boldsymbol{a}^{(0)}}$, $\varphi_{i,j}=\frac{\partial f}{\partial a_j}=\left.\frac{\partial f\left(x_i,\boldsymbol{a}\right)}{\partial a_j}\right|_{\boldsymbol{a}=\boldsymbol{a}^{(0)}}$, $j=1,2,\cdots,n$, $\Delta\boldsymbol{a}=\boldsymbol{a}-\boldsymbol{a}^{(0)}=\left(\Delta a_1,\Delta a_2,\cdots,\Delta a_n\right)^{\mathrm{T}}$, $\Delta a_1=a_1-a_1^{(0)}$, $\Delta a_2=a_2-a_2^{(0)}$,…, $-\Delta a_n=a_n-a_n^{(0)}$, $r_i^{(0)}=y_i-f\left(x_i,\boldsymbol{a}^{(0)}\right)$, $1\leq i\leq m$.

Substitute (5) into (4) and eliminate r_i:

$$\begin{cases}\sum_{i=i}^{m}\frac{1}{\left|r_i\right|}\varphi_{1,i}\left(\varphi_{1,i}\Delta a_1+\varphi_{2,i}\Delta a_2+\cdots+\varphi_{n,i}\Delta a_n\right)\approx\sum_{i=1}^{m}\frac{r_i^{(0)}}{\left|r_i\right|}\varphi_{1,i},\\ \sum_{i=i}^{m}\frac{1}{\left|r_i\right|}\varphi_{2,i}\left(\varphi_{1,i}\Delta a_1+\varphi_{2,i}\Delta a_2+\cdots+\varphi_{n,i}\Delta a_n\right)\approx\sum_{i=1}^{m}\frac{r_i^{(0)}}{\left|r_i\right|}\varphi_{2,i}, \qquad r_i\neq 0,\\ \vdots\\ \sum_{i=i}^{m}\frac{1}{\left|r_i\right|}\varphi_{n,i}\left(\varphi_{1,i}\Delta a_1+\varphi_{2,i}\Delta a_2+\cdots+\varphi_{n,i}\Delta a_n\right)\approx\sum_{i=1}^{m}\frac{r_i^{(0)}}{\left|r_i\right|}\varphi_{n,i}.\end{cases} \tag{6}$$

For the sake of simplicity, we define $\sum=\sum_{i=1}^{m}$, $\varphi_j=\varphi_{i,j}$ and use k as the iteration number:

$$\begin{pmatrix}\sum\frac{\varphi_1\varphi_1}{\left|r_i\right|} & \sum\frac{\varphi_1\varphi_2}{\left|r_i\right|} & \cdots & \sum\frac{\varphi_1\varphi_n}{\left|r_i\right|}\\ \sum\frac{\varphi_2\varphi_1}{\left|r_i\right|} & \sum\frac{\varphi_2\varphi_2}{\left|r_i\right|} & \cdots & \sum\frac{\varphi_2\varphi_n}{\left|r_i\right|}\\ \vdots & \vdots & & \vdots\\ \sum\frac{\varphi_n\varphi_1}{\left|r_i\right|} & \sum\frac{\varphi_n\varphi_2}{\left|r_i\right|} & \cdots & \sum\frac{\varphi_n\varphi_n}{\left|r_i\right|}\end{pmatrix}\begin{pmatrix}\Delta a_1\\ \Delta a_2\\ \vdots\\ \Delta a_n\end{pmatrix}=\begin{pmatrix}\sum\frac{r_i^{(k)}}{\left|r_i\right|}\varphi_1\\ \sum\frac{r_i^{(k)}}{\left|r_i\right|}\varphi_2\\ \vdots\\ \sum\frac{r_i^{(k)}}{\left|r_i\right|}\varphi_n\end{pmatrix}, \tag{7}$$

where: Δa_1, Δa_2,…, Δa_n represent micro variables and obey the following rule

$$a_1^{(k+1)}=a_1^{(k)}+\Delta a_1,\cdots,a_n^{(k+1)}=a_n^{(k)}+\Delta a_n,k=0,1,\cdots \tag{8}$$

The initial value of $\boldsymbol{a}^{(0)}$ can be custom but we recommend them to be the result of Least Squares method.

D. Algorithm flowchart

The specific algorithm calculation steps are shown in Fig. 1.

III. ESTIMATION OF EV OWNERSHIP

A. Logistic curve estimation model

To forecast the car ownership accurately, the Logistic curve which can reflect the growth and saturation characteristics is used to forecast the ownership [13].

The logistic curve shows that the variable's increasing rate keeps on increasing time by time first, and then it will decrease later. At last it will reach an extreme value.

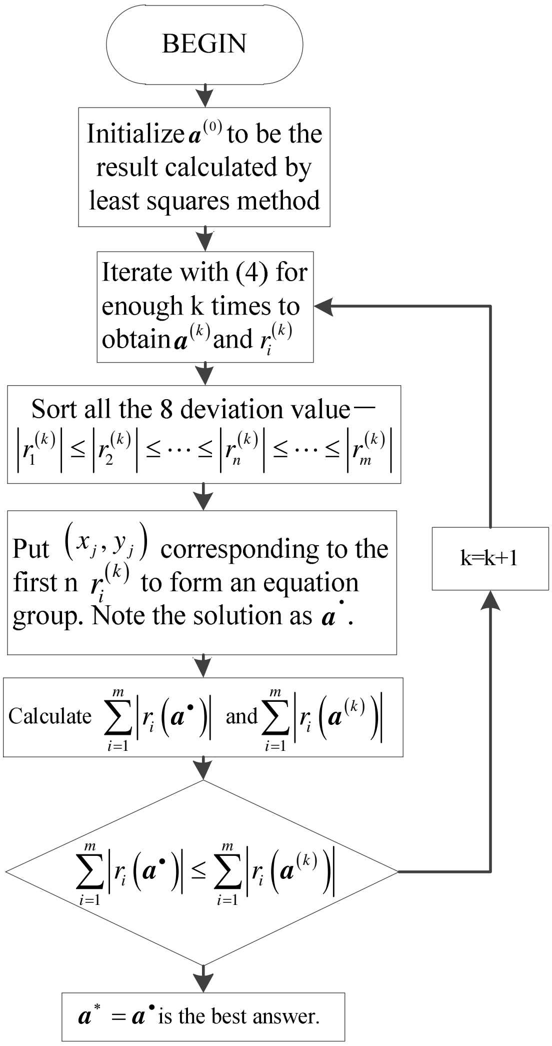

Fig. 1. The algorithm flowchart.

The logistic curve model we adopted in this paper is

$$y_i = f(x) = \frac{k}{1 + ae^{-bx_i}}, \tag{9}$$

where, y_i is the ith year's forecast value; x_i is the time corresponding to represent the ith year; a, b is coefficient; k is the extreme value (saturation value) of the curve. The coefficient a and b can be calculated by the following way.

Transform (8) into log form and suppose $y_i' = \ln(k / y_i - 1)$, $a' = \ln a$, $b' = -b$, $x' = x$ and then (8) is changed into

$$y_i' = a' + b'x_i'. \tag{10}$$

a' and b' need to be obtained by a linear regression equation, and the coefficients a and b can be calculated, and at last the equation is obtained. After the simulation and analysis through the Logistic curve, the number of ownership can be calculated too.

A. *Ownership estimation*

Before using LAD to regress, it is most important to confirm the value of k. In this paper, we define y_i as the per capital EV ownership so that we can find the saturation k easier.

The data of the per 1000 inhabitants vehicles ownership are shown in Fig. 2. From the curves in Fig. 2, we can find that the development of the vehicles in the four different countries follows the similar regular pattern. It is clear that this relationship is not linear or log-linear, but instead is more accurately represented by some sort of S-shaped curve. There are a number of different functional forms that can describe such a process, for example, the logistic, logarithmic logistic, cumulative normal, and Gompertz functions. After experimenting with a number of different functional forms, the Logistic model is chosen for the analysis [14]-[16].

In the future, we can expect the ownership to stop growing at the same saturation level which is about equal to 850 [17]. While in this paper, we mainly focus on the ownership of EV. Since EV cannot completely replace the use of fuel vehicles, the saturation level cannot reach the value of 850. For nowadays, America is approaching the saturation level while Japan and Korea is on their way of fast growing. China, owning to the encouraging policy, is accelerating to catch up those developed countries. According to the historical data over the past years and the policy of Chinese government, the saturation level will not be higher than 500. For the sake of comparison, another two saturation value 400 and 600 is used for the research.

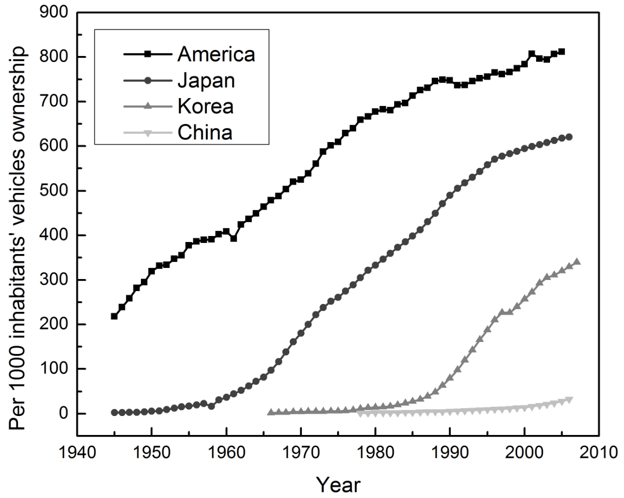

Fig. 2. Per 1000 inhabitants vehicles ownership of different countries.

B. *Estimation result*

With the method in Section II and (9), the estimation results can be easily achieved. What's more, Least Square (LS) method is also used for comparison. The regressions are made with the data of the vehicles' ownership in China from 1978 to 2010.

Result based on LS method

$$y' = -0.1125x' + 6.083\,. \tag{11}$$

Results based on LAD method:

$$\begin{aligned} y' &= -0.1067x' + 5.7502, \quad k = 0.4, \\ y' &= -0.1065x' + 5.9739, \quad k = 0.5, \\ y' &= -0.1064x' + 6.1565, \quad k = 0.6. \end{aligned} \tag{12}$$

Fig. 3 gives the true values and the results based on LAD and LS methods. In this case, the results of LAD method are close to LS method but more accurate as is shown in Table I.

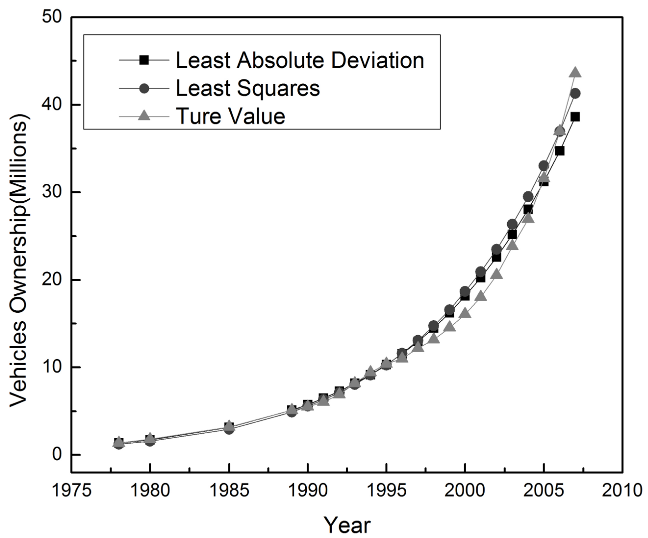

Fig. 3. The true value and regression results of two methods in fitting the historical data of vehicles in China.

Fig. 4 shows the estimation results under different saturation level k. The results depict that the development of vehicles in China will be steadily growing whatever the saturation will be.

TABLE I THE MEAN RELATIVE ERRORS OF TWO METHOD IN THE FITTING.

	LAD(k=0.4)	LAD(k=0.5)	LAD(k=0.6)	LS(k=0.5)
Relative Error	5.57%	5. 56%	5.59%	7.42%

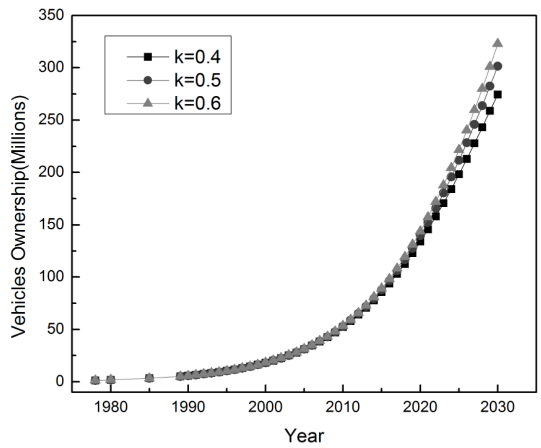

Fig. 4. Estimation results of prospective vehicles ownership under different saturation levels.

IV. SIMULATION OF CHARGING LOAD IN DEMONSTRATION DISTRICT

A. *The Scale of Demonstration District*

Assume that the demonstration district have 100 families which have three people each. In this way, there are about 300 people and the number of EV, according to Section III, is nearly 60 in the year of 2030.

Reference [18] provides us different users' habits of driving EV. It exactly describes a common situation (mostly charging habits) of EV. In the following study, our simulation is completely based on the survey.

Assume that the current of conventional charge and fast charge are 0.2C and 1.25C. What's more, it respectively takes about 5 hours and 0.8 hours to be fully charged. And the charge powers are 7kW and 45kW accordingly.

B. *Simulation results*

According to the assumed scenarios, two groups of simulation curves for summer and winter respectively are simulated as shown in Fig. 5(a), 5(b) and Table II. Through the simulations we can know that the possible daily maximum load caused by disorderly charging will be extremely high. Under some coincident situations, the load even doubles.

V. RECONSTRUCTION OF THE DISTRIBUTION NETWORK

A. *Distribution transformers*

According to "The Code on The Technology of Distribution Network" of State Grid Corporation of China, if the construction area is less than $120m^2$, the capacity configuration per family is 8kW. Therefore, 100 families are at the load level of about 800kW.

To get the value of capacity configuration of transformer, we have the equation

$$P_T = \sum P_i \times K_p \,, \quad (6)$$

where P_T represents the capacity configuration of transformer in the demonstration district; P_i represents the load of different consumer equipment; K_p represents the coefficient of transformer's capacity and the maximum load and in this case it should be 0.6 [19].

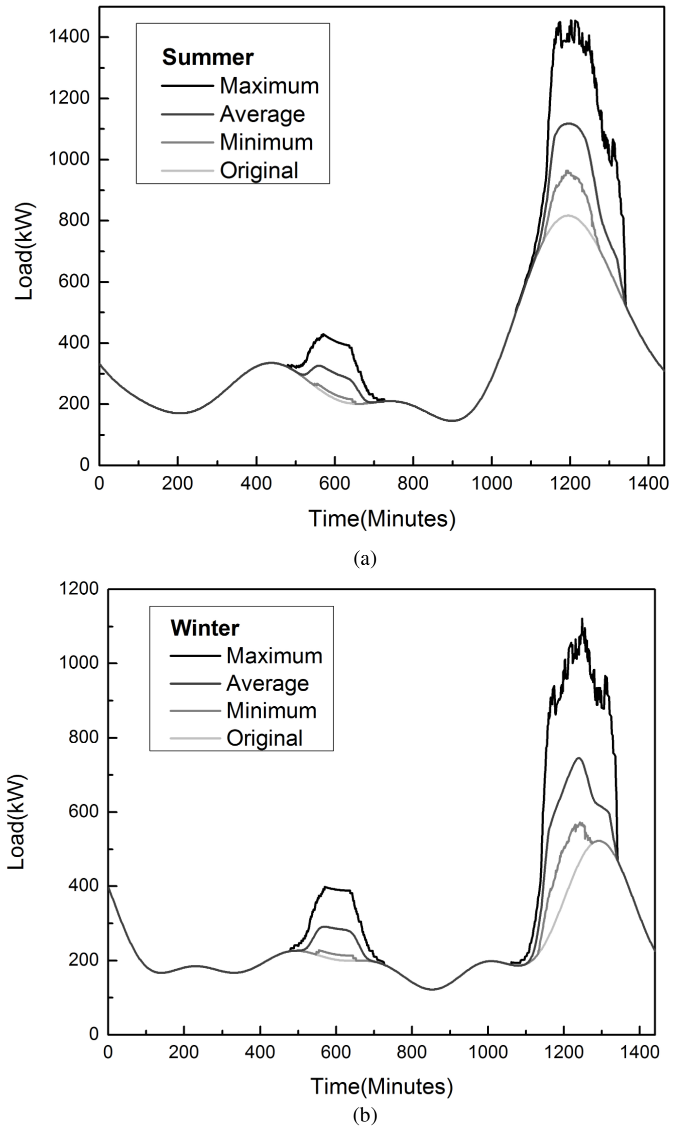

Fig. 5. Estimation load with EV for summer (a) and winter (b).

After the calculation, we get the power need for reconstruction as shown in Table III. The residential transformer used in this demonstration district has a capacity of 1000kVA.

TABLE II. MAXIMUM LOAD OF SIMULATION.

Maximum Load	Maximum	Average	Minimum
Summer	1492	1118	957.1
Winter	1103	745.9	591.3

TABLE III. LOAD REQUEST FOR DISTRIBUTION TRANSFORMER.

Maximum Load	Maximum	Average	Minimum
Summer	1865	1397.5	1196.4
Winter	1378.8	932.4	739.125

In the worst case (maximum situations) of summer residential distribution transformer needs an 86.5% increase of its capacity. Even in normal circumstances, it needs an advance of nearly 40%. Although in the lowest case, nearly 20% increase is necessary. On the contrary, winter only request to upgrade the transformer capacity in the highest case. In the rest of the case, the transformer used will be able to meet the requirements of prospective situation.

B. Lines

The charge load brings the problem of heavy circuit to the distribution network. So the lines in the network also should be upgrades. Incoming lines may be replaced by cables; the type and pattern of the overhead lines may be changed to suit new requests.

VI. CONCLUSIONS

In this study, prospective EV ownership is analyzed based on LAD method using the historical data of China. The Lad method is not widely used because of its difficulty to calculate and we solve the problem through approximately value. The LAD method shows its advantage in regression compared to Least Squares method. The estimation results under different levels show that the saturation level will not impact on the development of EV in recent years. Then based on the estimation results, we simulate the load when EV begin to charge in the demonstration district. The simulation results depict that the residential distribution transformers should be upgraded considering the high load in summer as well as lines in the district.

REFERENCES:

[1] Q. Xu, N. Wang, K. Yukita, Y. Goto, K. Ichiyanagi, "Developed Modeling and Numerical Simulation for Mismatching Photovoltaic Performance Evaluation", *IEEJ Trans. Electrical and Electronic Engineering*, vol. 4, pp. 545–552, 2009. [Online]. Available: http://dx.doi.org/10.1002/tee.20441

[2] H. Zang, Q. Xu, H. Bian, "Generation of typical solar radiation data for different climates of China", *Energy*, vol. 38,pp. 236–248, 2012. [Online]. Available: http://dx.doi.org/10.1016/j.energy.2011.12.008

[3] W. D. Fisher, "A Note on Curve Fitting with Minimum Deviations by Linear Programming", *Journal of the American Statistical Association*, vol. 56, pp. 359–362, 1961. [Online]. Available: http://dx.doi.org/10.1080/01621459.1961.10482119

[4] S. Portnoy, R. Koenker, "The Gaussian Hare and the Laplacian Tortoise: Computability of Squared–Error versus Absolute–Error Estimators", *Statistical Science*, vol. 12, pp. 279–296, 1997. [Online]. Available: http://dx.doi.org/10.1214/ss/1030037960

[5] A. Giloni, B. Sengupta, J. S. Simonoff, "A mathematical programming approach for improving the robustness of least sum of absolute deviations regression", *Wiley Subscription Services*, vol. 53, pp. 261–271. 2006.

[6] J. Ahn, G. Jeong, Y. Kim, "A forecast of household ownership and use of alternative fuel vehicles: A multiple discrete–continuous choice approach", *Energy Economics*, vol. 30, pp. 2091–2104, 2008. [Online]. Available: http://dx.doi.org/10.1016/j.eneco.2007.10.003

[7] R. Segal, "Forecasting the market for electric vehicles in California using conjoint analysis", *Energy Journal*, vol. 16, p. 89, 1995. [Online]. Available: http://dx.doi.org/10.5547/ISSN0195-6574-EJ-Vol16-No3-4

[8] J. Wang, K. Wu, Z. Liu, F. Wang, Y. Zhao, "Impact of plug–in hybrid electric vehicles on power distribution networks", in *Proc. of 4th International Conference on Electric Utility Deregulation and Restructuring and Power Technologies*, 2011, pp. 1618–1622.

[9] K. Clement–Nyns, E. Haesen and J. Driesen, "The Impact of Charging Plug–In Hybrid Electric Vehicles on a Residential Distribution Grid", *IEEE Trans. Power Systems*, vol. 25, pp. 371–380, 2010. [Online]. Available: http://dx.doi.org/10.1109/TPWRS.2009.2036481

[10] V. Nerenberg, M. Bernard III, N. Collins, "Evaluation Results of San Francisco Bay Area Station–Car Demonstration", *Transportation Research Record: Journal of the Transportation Research Board*, vol. 1666, pp. 110–117, 1999. [Online]. Available: http://dx.doi.org/ 10.3141/1666-13

[11] A. Charnes, W. W. Cooper, R. O. Ferguson, "Optimal estimation of executive compensation by linear programming", *Management Science*, vol. 1, pp. 138–151, 1955. [Online]. Available: http://dx.doi.org/10.1287/mnsc.1.2.138

[12] L. Gu, "Least absolute deviation method of curve fitting", *Tongji Daxue Xuebao/Journal of Tongji University*, vol. 39, pp. 1377–1382, 2011.

[13] Y. He, Y. Jiao, Y. Li, "Residential load forecast in China", in *Proc. of Power Engineering Conference*, 2007, pp. 686–691.

[14] P. Kadar, R. Lovassy. "Spatial load forecast for Electric Vehicles", in *Proc. of 4th IEEE International Symposium on Logistics and Industrial Informatics (LINDI 2012),* Smolenice, Slovakia, 2012. [Online]. Available: http://dx.doi.org/10.1109/LINDI.2012.6319481

[15] Z. Mohamed, P. S. Bodger, "A variable asymptote logistic (VAL) model to forecast electricity consumption", *International Journal of Computer Applications in Technology*, vol. 22, pp. 65–72, 2005. [Online]. Available: http://dx.doi.org/10.1504/IJCAT.2005.006937

[16] Z. Mohamed, P. Bodger, "A comparison of Logistic and Harvey models for electricity consumption in New Zealand", *Technological Forecasting and Social Change*, 2005, vol. 72, pp. 1030–1043. [Online]. Available: http://dx.doi.org/10.1016/j.techfore.2004.05.002

[17] J. Dargay, D. Gately, "Income's effect on car and vehicle ownership, worldwide: 1960-2015", *Transportation Research Part A: Policy and Practice*, vol. 33, pp. 101–138, 1999. [Online]. Available: http://dx.doi.org/10.1016/S0965-8564(98)00026-3

[18] J. Taylor, A. Maitra, M. Alexander, D. Brooks, M. Duvall, "Evaluation of the impact of plug–in electric vehicle loading on distribution system operations", in *Proc. of Power & Energy Society General Meeting*, 2009, pp. 1–6.

[19] *The Standard of Power Supply Distribution Facilities Constructing for Residential Districts* (DGJ32/J11－2005), Ministry of Housing and Urban–Rural Development of Jiangsu Province, 2005.