EV Regional Market Sales Forecast Based On GABP Neural Network

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Abstract. In view of the complexity and particularity of the EV regional market, GABP neural network algorithm is introduced to build a sales forecasting model of sub-models for the EV regional market. And then, the model was used to forecast the sub-models sales of three types of hypothetical development scenarios for the EV market in 2020. The results show that the restricted-purchase cities still are the major potential EV market in the future, and followed by cities such as Wuhan, Qingdao, and Taiyuan; In terms of models, A-class EV will become the main potential model for 2020.

1. Introduction
With the shortage of energy and the increasing pollution of the environment, more and more countries have begun to implement the “Green New Energy Plan” to develop the electric vehicle industry. It is of great strategic significance to develop electric vehicles to enhance the international competitiveness of China's automobile industry.

From the development law of automobile industry, it is very important to predict the automobile sales and potential models in regional markets, which can provide systematic theoretical guidance for the development strategies of the government, industry and enterprises [1]. By understanding the most important factors affecting regional market sales, local governments can identify the deficiencies and excesses in the promotion of electric vehicles, thereby helping the government optimize the promotion strategy of electric vehicles. By forecasting the sales volume and potential models of regional markets, OEMs can develop appropriate regional layout promotion and model development strategies to improve the industry competitiveness of enterprises.

This paper analyzes the impact factors in the development of the electric vehicle in regional markets, and establishes a predictive model of the sales volume and potential models, then provides development advices for governments and OEMs from the aspects of resource allocation, model development and regional layout strategy.

2. EV sales forecasting model construction

2.1. Methodologies
Desk research method, Questionnaire method and Grey Relational Analysis are used to determine the main influencing factors affecting EV sales volume and obtain the impact factor database. GA-BP
neural network algorithm is used to build regional market EV sales and potential model forecasting model to analyze future sales volume, providing strategic advices for local governments and OEMs.

2.2. Main influencing factors identification and collection

Based on the research on the influencing factors of EV sales volume at home and abroad [2-9], this paper divides the influencing factors into the following three categories: policy, consumer and society. Since the purpose of this paper is to analyze the development of EV market in different cities, it is necessary to select the influencing factors with obvious regional differences and independent of each other for quantitative analysis, and finally select the following seven influencing factors (see Table 1.). There is a correlation between influencing factors, but no direct causal relationship.

Table 1. EV regional market influencing factors.

| Category      | Influencing factor                      |
|---------------|----------------------------------------|
| Policy        | EV unlimited purchasing policy factor¹ X₁ |
| Consumer      | Purchase power X₂                       |
|               | GDP per capita X₃                       |
|               | EV acceptance X₄                       |
|               | Model preference X₅                     |
| Society       | Urbanization rate X₆                    |
|               | Public charging infrastructure density² X₇ |

Note: ¹EV unlimited purchasing policy factor $X_1 = \frac{e_{NEV}}{e_{ICE}}$, New energy vehicle lottery winning rate / bid winning rate, unit: %. ²Public charging infrastructure density $X_7 = \frac{N}{S}$, number of city’s charging piles. S, urban area, unit: m².

EV acceptance and Model preference can be obtained by Questionnaire method. Other factors can be obtained from relevant annual reports and government documents.

2.3. EV regional market sales forecasting model construction

2.3.1. Model principle and construction. The steps of constructing the EV regional market sales forecasting model using GABP neural network [10] are as follows:

(1) The topology of the BP neural network is shown in Figure 1.

(2) Initialize the network weight threshold: Let the learning frequency $t=0$, the initial value of each weight and threshold is a random number in the interval of (-1, 1), $w_{ij}(t) \in [-1,1]$, $\theta_j(t) \in [-1,1]$, $\theta_k(t) \in [-1,1]$.

(3) Use genetic algorithms to optimize threshold values for each connection layer.

(4) Assign the optimal individual obtained in 3) to the initial weight threshold of each connection layer in the BP neural network.

(5) Use BP neural network to forecast
Figure 1. EV regional market sales forecasting model’s topology.

(a) Forward calculation
1) Input a training tuple \((X_k, T_k)\), \(k \in \{1,2,...,N\}\). \(N\) is the total number of training tuples, \(X_k \in \mathbb{R}^n\), \(T_k \in \mathbb{R}^m\).

2) Calculate the output value of the hidden layer unit (where the excitation function uses a bipolar S-type function)
\[
Y_j^2 = f \left( \sum_{i=1}^{n_2} w_{ij} Y_i^1 - \theta_j \right) = f \left( \sum_{i=1}^{n_2} w_{ij} X_{ki} - \theta_j \right), \quad j \in \{1,2,...,n_1\}
\]  
(1)

3) Calculate the output value of the output layer unit:
\[
Y_k^3 = f \left( \sum_{j=1}^{n_3} w_{jk} Y_j^2 - \theta_k \right), \quad k \in \{1,2,...,n_2\}
\]  
(2)

4) Calculate the output layer node error:
\[
\delta_k = (T_k - Y_k^3) Y_k^3 (1 - Y_k^3), \quad k \in \{1,2,...,n_2\}
\]  
(3)

5) Calculate hidden layer node error:
\[
\delta_j = Y_j^2 (1 - Y_j^2) \sum_{k=1}^{n_2} \delta_k w_{jk}
\]  
(4)

6) Use the error correction amount \(\delta_{lk}\) to correct the connection weight matrix \(w_{jk}\) and the threshold vector \(\theta_k\) between the hidden layer and the output layer.
Use the error correction amount $\delta_j$ to correct the connection weight matrix $w_{ij}$ and the threshold vector $\theta_j$ between the hidden layer and the output layer:

$$w_{ij}(t+1) = w_{ij}(t) + \alpha \delta_j Y_j^2$$

$$\theta_j(t+1) = \theta_j(t) + \beta \delta_j$$

7) If all training samples have not been taken, return step 2), otherwise, calculate the error function $E$:

$$E = \frac{1}{2} \sum_{k=1}^{N} \| Y_k - Y_k^{\hat{}} \|^2$$

8) If $E$ is below the specified upper error limit or reaches the specified number of learnings, the algorithm ends; otherwise, the number of learnings is $t=t+1$, and returns to step 1.

2.3.2. Model verification. The first 42 sets of data (about 70%) in Table 2 were selected as training samples, and the last 18 sets of data (about 30%) were used as test samples to train the network. Figure 2. Is a comparison chart between the predicted and actual value of the EV sales, where * represents the predicted value and ○ represents the actual value. It can be seen that the trend between the predicted and actual values of the BP neural network is basically the same.

After learning, training, and forecasting the sales and influencing factor data of the EV regional market in 2016 by using the network model, the predicted value of the sales volume is compared with the actual value to comprehensively evaluate the performance of the network model. This paper uses the following indicators for evaluation:

$$\Delta_j = y_j^k - o_j^k$$

Where $o_j^k$ represents the actual value, $y_j^k$ represents the predicted value.

The absolute error value of the prediction result is shown in Figure 3.
Figure 3. Absolute error value between predicted and actual sales of EV

It can be seen from Fig. 3 that the accuracy of the electric vehicle regional market sales and vehicle potential prediction model established by BP neural network based on genetic algorithm optimization is good, and the maximum absolute error is less than 300 vehicles, which can basically meet the actual application needs of EV sales forecast.

Therefore, it can be seen that the forecasting model established by the GABP neural network method can better predict the sales volume of different segments of EV in different regional markets, and has good application value.

3. 2020 domestic EV regional market sales and potential model forecast

3.1. Scenario assumption

From the previous forecasting results, as long as we know the 7 influencing factors at a corresponding time point in a certain region, we can build an EV regional market sales forecasting model. Therefore, in order to forecast the development of the regional market for EV in 2020, it is necessary to study the development of various influencing factors in 2020.

In view of the changes in the influencing factors of EV in the future, this paper has set up three scenarios: pessimistic scenario, general scenario and optimistic scenario. The corresponding indicators for each scenario are assumed as shown in Table 2. Below:

| Factor                        | Pessimistic                      | General                         | Optimistic                      |
|-------------------------------|----------------------------------|---------------------------------|---------------------------------|
| EV unlimited purchasing policy| a. the purchase of EV is restricted | a. the purchase of EV is not restricted | a. the purchase of EV is not restricted |
|                               | b. the bidding rate of ICE and EV is down 5% year by year | b. the bidding rate of ICE is down 5% year by year | b. the bidding rate of ICE is down 10% year by year |
|                               | c. the unlimited purchasing policy remains unchanged | c. the unlimited purchasing policy increases 5% year by year | c. the unlimited purchasing policy increases 10% year by year |
| Population                    | CAGR: 0%                         | CAGR: 5%                        | CAGR: 10%                       |
| GDP per capita                 | CAGR: 6%                         | CAGR: 8%                        | CAGR: 10%                       |
| EV acceptance                  | CAGR: 10%                        | CAGR: 20%                       | CAGR: 30%                       |
| Model preference              | Refer to consumer survey result  |                                 |                                 |
| Urbanization rate              | CAGR: 3%                         | CAGR: 5%                        | CAGR: 7%                        |
| Public charging infrastructure density | CAGR: 10%                     | CAGR: 30%                       | CAGR: 50%                       |
3.2. Sales forecasting results and analysis
The total sales forecasting results of various regional markets in different scenarios in 2020 are shown in Figure 4.
We can get the following conclusion:

1) Although Beijing’s sales growth rate is not high, it is still the largest potential market for EV. Its sales volume of EV in 2020 can reach 49,000 to 59,000 vehicles.

2) In 2020, cities with restricted purchasing policy remain the main potential market for EV, including Tianjin, Shenzhen, Shanghai, Guangzhou and Hangzhou.

3) The main potential cities in tier 1 and tier 2 cities are Wuhan, Qingdao, Taiyuan, etc. The economic development level of these cities is good, and they all run electric vehicle public demonstration operation project, such as BYD electric taxis in Wuhan and Taiyuan, EV car sharing projects in Qingdao, which have increased consumers’ acceptance of EV. In 2020, sales of EV can reach 2000 to 5000 vehicles.

4) In some small and medium-sized cities, such as Nanchang, Shangrao and Jinhua, the development of EV is insufficient. The sales growth is slower than that in 2016, and there are even negative growth phenomena.

3.3. Sales forecasting results and analysis
It can be seen that the main potential cities for EV in 2020 are: Beijing, Tianjin, Shenzhen, Shanghai, Hangzhou, Guangzhou, Wuhan, and Qingdao. For this part of cities, the forecasting results of their potential models are as follows:
Figure 5. Forecasting results of potential model in different scenarios in main potential cities in 2020.
As can be seen from Figure 5, the main models of most cities in 2020 are A0 and A-segment models.

Tianjin, Shanghai, Hangzhou, Wuhan and Qingdao are suitable for promoting A00-segment models, while Beijing and Guangzhou are not suitable for promoting A00-segment models.

Beijing, Tianjin, Shenzhen, Hangzhou and Guangzhou are suitable for promoting B-segment and above models, and cities such as Wuhan, Qingdao, and Taiyuan are not suitable for promoting B-segment and above models.

4. Suggestions for EV promotion for governments and OEMs

For local governments, it is difficult to promote EV in regional markets by relying only on financial subsidies, and it is necessary to strengthen the construction of public charging infrastructure. In addition, it is necessary to introduce demonstration projects of electric vehicles in the public domain, such as electric car taxis, electric car sharing and other projects, to enhance consumers' understanding and awareness of electric vehicles, thereby increase consumers' acceptance of electric vehicles and ultimately promote development of electric vehicles in regional markets.

For OEMs, the ICE-limited cities are still the first choice for the layout of EV dealerships, followed by cities with good charging infrastructure, such as Wuhu and Taiyuan. In addition, they can also choose cities which have public electric demonstration projects, such as Taiyuan, Qingdao. As consumers' acceptance of electric vehicles increases, A0 and A-segment electric vehicles will become the primary demand for consumers after 2020. In terms of regions, tier 1 ICE-limited cities’ consumers are more inclined to buy A0 and above models, while tier 2 and tier 3 cities are the best markets to promote A00-segment models. OEMs can also actively promote their own brand electric vehicle public demonstration projects to improve consumers’ understanding and recognition of their own brand electric vehicles, so as to promote consumers to buy their own brand electric vehicles.

References

[1] LIU Yingqi, WANG Meng, WANG Jingyu. "The Predictive Research on China's New Energy Vehicles Market." Research on Economics and Management 37.4 (2016): 86-91.

[2] LI Ying, HU Jian. "An Agent-Based Diffusion Modeling and Simulation of Multiple Classes of New Energy Vehicles." Journal of Systems & Management 23.5 (2014): 711-716.

[3] Nijhuis, J., and S. van den Burg. "Consumer-oriented strategies in new car purchasing." Conference Proceedings: Workshop of the Sustainable Consumption Research Exchange (SCORE) Network. Cases in Sustainable Consumption and Production, Paris. 2007.

[4] Schwoon, Malte. "Simulating the adoption of fuel cell vehicles." Journal of Evolutionary Economics 16.4 (2006): 435-472

[5] Bapna, Ravi, Lakshman S. Thakur, and Suresh K. Nair. "Infrastructure development for conversion to environmentally friendly fuel." European Journal of Operational Research 142.3 (2002): 480-496.

[6] Ozaki, Ritsuko, and Katerina Sevastyanova. "Going hybrid: An analysis of consumer purchase motivations." Energy Policy 39.5 (2011): 2217-2227.

[7] Carley, Sanya, et al. "Intent to purchase a plug-in electric vehicle: A survey of early impressions in large US cites." Transportation Research Part D: Transport and Environment 18 (2013): 39-45.

[8] Knez, Matjaz, Borut Jereb, and Matevz Obrecht. "Factors influencing the purchasing decisions of low emission cars: a study of Slovenia." Transportation research Part D: Transport and environment 30 (2014): 53-61.

[9] WANG Ning, YAN Run-lin, LIU Ya-fei. "Identifying Consumer Characteristics and Public Acceptance of Electric Vehicles in China." China Soft Science 10 (2015): 70-84.

[10] LIU Huanjie. Fuzzy Neural Network Techniques Based on GA and Applications to Sales Forecasting. Northeast University, 2005.