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A Method for Electric Vehicle Ownership Forecast Considering Different Economic Factors

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Abstract

The construction of electric vehicles (EVs) charging station needs to be planed according to the ownership of EVs, traffic condition, population etc. Therefore a BP neural network based method to forecast the EV ownership for a city is presented in the paper, which considers the influence on the EV ownership caused by many related economy factors, including GDP of a city, vehicle production, per capita crude steel production, per capita generation capacity, road passenger traffic, highway mileage and the total population. A BP neural network is set up for the forecast of EV ownership, and the input layer contains seven neutrons, which represent different economic factors. There are three neurons in its hidden layer, and the output is the EV ownership. Then the method to predict the EV ownership of a city is presented, which is based on the forecast of the civilian car ownership in a city and the country. The EV ownership in the city of Chongqing from the year 2013 to 2020 is predicted, and the accuracy of the model is verified firstly, then the EV ownership in Chongqing is obtained, which is helpful to make plans for the development of electric vehicle.

Keywords*: ownership, BP neural network, electric vehicle, civilian car ownership*

1. Introduction

Reducing dependence on the crude oil and emissions of carbon dioxide and particulates are among the leading reasons that electric vehicles (EVs) are increasing in popularity. Most EVs are planned to have a fully electric range between 10-40 miles, which is within the daily commute distance of the average driver [1]. Ultimately, EVs will shift energy demands from crude oil to electricity for the personal transportation sector. To promote the development of EVs, many charging stations have been built, and more and more will be built [2-5].

Meanwhile many studies regarding EVs are being conducted, including the design and optimization of charging stations, investigation on the control of vehicle-to-grid (V2G) [1] [6-12], analysis on the influence caused by the charging machines [13-16], energy storage of EV, charging techniques [17-20], and so on. In China the national grid has started the construction of charging station since 2009, which aims at fasting the promotion of EVs.

For the construction of charging station and other facilities related to EVs, a better planning will increase the economy benefits. Therefore it is necessary to get the ownership of the electric vehicles, with which we can make reasonable plans for the construction of charging station, strategies, etc. The forecast of the ownership of EVs is conducted based on the statistical ownership of the EVs. However the development of electric vehicles is still at the initial stage, hence there is not enough statistical data for the forecast of the ownership of EVs.

In this study, a method based on BP neural network to forecast the long-term EV ownership for a city is presented, which considers the influence on the EV ownership caused by many related economy factors, including GDP of a city, vehicle production, per capita crude steel production, per capita generation capacity, road passenger traffic, highway mileage and the total population. A BP neural network is set up for the forecast of EV ownership, and the input layer contains seven neutrons, which represent different economic factors. There are three neurons in its hidden layer, and the output is the EV ownership. Then the method to predict the EV ownership of a city is presented, which is based on the forecast of the civilian car ownership

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in a city. The EV ownership in Chongqing from the year 2013 to 2020 is predicted, and the accuracy of the model is verified firstly, then the EV ownership in Chongqing is obtained, which is helpful to make plans for the development of electric vehicle.

2. Basics of BP Neural Network

2.1. BP Neural Network

BP neural network [1] [6-10] is a multi-layer hierarchical neural network with upper neurons fully associated with lower neurons. When a couple of learning samples are supplied to the network, the transferred value is propagated from the input layer through middle layer to the output layer, and we can get neural network input response from neurons in output layer. Along the direction of reducing the error between expected output and actual output, connection weights are adjusted from the output layer to every middle layer, and ultimately to the input layer. With the ongoing amendment by this back-propagation, the correct rate for the network response to input also increases continuously. As BP algorithm implements middle hidden layer and has a corresponding learning rules to follow, it has the ability to identify the non-linear pattern. Especially to those learning that has clear calculation methods and well-defined steps, BP algorithm has more extensive applications.

A BP neural network is usually composed of input layer, hidden layer (middle layer) and output layer as shown in Figure 1. For some practical problems, many hidden layers may be used. According to the structure of BP neural network, the learning information of BP is forward propagation, and the error is back propagation. Hence the main process of BP is comprised of two parts: the forward calculation on the input information and backward calculation on the error.

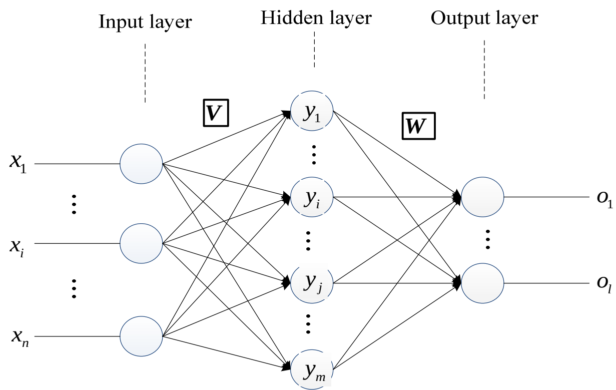

Figure 1. Structure of BP Neutral Network

2.2. Process of BP Neural Network

The neurons in the input layer collect the information and transfer the information to the neurons in the hidden layers. Then calculation on the input information in input layer will be carried out in the hidden layer. The structure of hidden layer usually is designed according to the characteristics of the input information. Finally the results obtained in the hidden layer are transferred to the output layer, now the forward learning process is finished [7, 8].

If the error between the output value and the objective is great, the backward error calculation and amendment will be started. Firstly the error will be transferred to the output layer then the weights for each layer will be changed according to gradient descent method. This process will be repeated until the error satisfies the criterion.

BP neural network learning rule is a supervised learning method, so a certain number of training samples are needed which are the standard input and output vectors. Figure 2 is the process of the weights adjustment, here $d_k(n)$ is the objective, $y_k(n)$ is the output and $e_k(n)$ is the error.

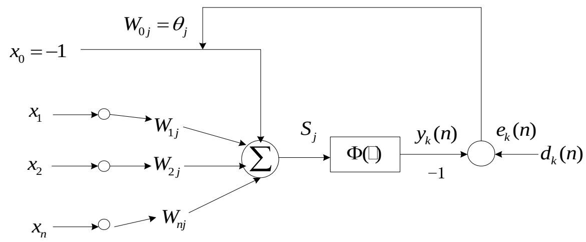

Figure 2. The Process of Error Correction

2.3. Algorithm of BP Neural Network

The algorithm used in BP neural network contains two parts: the first part is the calculation of error and amendment of weights for the output layer, the second part is the calculation of error and amendment of weights in the hidden layer. To simplify the analysis, here we take the BP neural network containing only one hidden layer for an example to formulate the equations used in BP network.

For the BP neural network containing one hidden layer, the error E between the output and the objective is as follows:

$$E = \frac{1}{2}(\boldsymbol{d} - \boldsymbol{O})^2 = \frac{1}{2}\sum_{k=1}^{l}(d_k - o_k)^2 \tag{1}$$

Expand the error *E* to the hidden layer, then we can calculate *E* as follows:

$$E = \frac{1}{2}\sum_{k=1}^{l}[d_k - f(net_k)]^2 = \frac{1}{2}\sum_{k=1}^{l}[d_k - f(\sum_{j=0}^{m} w_{jk} y_j)]^2 \tag{2}$$

And for the input layer, the error *E* is:

$$E = \frac{1}{2}\sum_{k=1}^{l}\{d_k - f[\sum_{j=0}^{m} w_{jk} f(net_j)]\}^2 = \frac{1}{2}\sum_{k=1}^{l}\{d_k - f[\sum_{j=0}^{m} w_{jk} f(\sum_{i=0}^{m} v_{ij} x_i)]\}^2 \tag{3}$$

It can be concluded that the error *E* in the input layer is the function of w_{jk} and v_{ij}, here w_{jk} and v_{ij} are the weight for the hidden layer and input layer respectively. Hence the error *E* can be changed by amending the weights. The purpose to amend the weights is to decrease the error, therefore the adjustment of the weights should be proportional to the gradient of the error, which are described as follows:

$$\Delta w_{jk} = -\eta \frac{\partial E}{\partial w_{jk}} \qquad j = 0, 1, \cdots, m; \qquad k = 1, 2, \cdots, l \tag{4}$$

$$\Delta v_{ij} = -\eta \frac{\partial E}{\partial v_{ij}} \qquad i = 0, 1, \cdots, n; \qquad j = 1, 2, \cdots, m \tag{5}$$

Where η is a constant, ranging from 0 to 1.

3. Model for the long-term Forecast of EV Ownership

3.1 Method to Forecast the EV Ownership

The prediction of EV ownership needs historical and statistical data as the sample data. However, the development of the electric vehicle is still in the initial stage, the historical data is not enough for an accurate forecasting, therefore it is difficult to forecast the ownership of electric vehicle.

For the construction of the charging stations in a city, we need to make a short-term planning and long-term planning, which can help to increase the economic benefit of the charging stations. Hence it’s necessary to forecast the ownership of the electric vehicle. To promote the development of electric vehicle, the Chinese government has made a series of strategies and plans for the development of electric vehicles, in which the EV ownership in China for 2015, 2020 are aimed to be 2.66 million and 16.98 million respectively.

The government will take many measures to achieve the aim of EV ownership in China. Hence the forecast of the EV ownership of a city can be conducted based on the EV ownership for the whole country, which is predicted by the government. The process for the forecast of EV ownership of a city is as follows:

1. Forecast the long-term civilian car ownership of a city according to its historical and statistical data based on BP neural network.
2. Forecast the long-term civilian car ownership of the country according to the country’s historical and statistical data based on BP neural network.
3. Calculate the EV ownership for each year in the future based on cubic Hermite interpolation and the ownership planning by the government.
4. According to the long-term civilian car ownership of the city and the country and planning EV ownership of the country, the long-term EV ownership of the city can be calculated as follows.

$$C_{EV\_city} = C_{EV\_country} * \frac{C_{car\_city}}{C_{car\_country}} * \lambda \qquad (6)$$

Where C_{EV_city} is the EV ownership of a city, $C_{EV\_country}$ is the EV ownership of the country, C_{car_city} is the civilian car ownership of the city and $C_{car\_country}$ is the civilian car ownership of the country. λ is a coefficient indicting that the difference of the strategies on the promotion of electric vehicle between a city and the country.

3.2. BP Neural Network for the Forecast of Car Ownership

To forecast the EV ownership of a city, the civilian car ownership of a city and the country should be forecast firstly, which is predicted by BP neural network.

The ownership of civilian car not only depends on the historical data of civilian car ownership, but also on other statistical data of the economy, including Gross Domestic Product (GDP), vehicle production, per capita crude steel production, per capita generation capacity, road passenger traffic, highway mileage and the total population. Hence all these statistical data need to be considered in the forecast of civilian car ownership.

In this study, the input layer of BP neural network is comprised of all the factors listed above and the historical civilian car ownership, and only one hidden layer is used. The count of neurons in the hidden layer is $l = \sqrt{n+m}$, here n is the count of neurons in the input layer, and m is the count of neurons in the output layer. Statistical data in the past 20 years are used as training samples. Figure 3 is the BP neural network for the forecast of civilian car ownership. There are three neurons in the hidden layer, the output is the civilian car ownership.

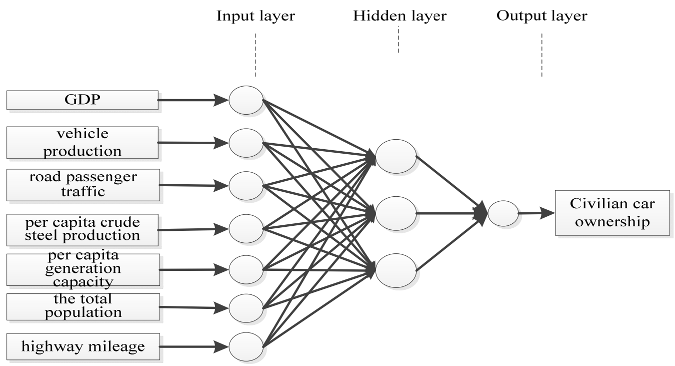

Figure 3. BP Neutral Network For The Forecast Of Civilian Car Ownership

For the forecast of civilian car ownership, the data in the past 20 years are taken as the training samples, and the error between the output and real value is computed as follows:

$$e(k) = \frac{|y(k) - y_0(k)|}{y_0(k)} \times 100\% \tag{7}$$

$$\sigma = \sqrt{\sum_{i=1}^{N} \frac{(e(k)/100)^2}{N}} \tag{8}$$

where $y(k)$ is the predicted civilian car ownership, $y_0(k)$ is the statistical civilian car ownership, $e(k)$ is the relative error between them, σ is mean square error and N is the years to be forecast.

4. Forecast of EV Ownership in the City of Chongqing

To verify the method presented in the paper, the EV ownership in Chongqing is predicted based on the statistical data from the year 1991 to 2010 as listed in the Appendix [12]. Firstly the civilian car ownership of Chongqing and the country is predicted, and the relative error for the prediction is analyzed.

4.1. Forecast of the Civilian Car Ownership

Table I shows the comparison of civilian car ownership between the statistics and calculated value in China from the year 2004 to 2010, and the relative error is shown in Figure 4. The maximum relative error is less than 2%, hence the accuracy of the forecast method is acceptable.

Table 1. Comparison of Civilian Cars Between the Calculated Values and Statistics (Unit: Million)

Year	2004	2005	2006	2007
Statistics	26.9371	31.5966	36.9735	43.5836
Calculated value	27.4092	31.8295	36.9626	42.9235
Year	2008	2009	2010	
Statistics	50.9961	62.8061	78.0183	
Calculated value	51.8120	63.2632	78.3105	

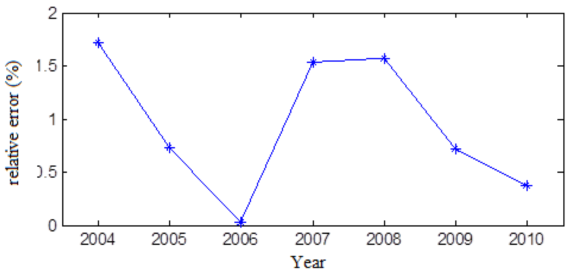

Figure 4. Relative Error of Predicted Value and the Real Value

Table 2. Ownership of Civilian Car in China from 2013 to 2020 (Unit: million)

Year	2013	2014	2015	2016
Civilian car ownership	105.267	122.2433	141.9573	164.8506
Year	2017	2018	2019	2020
Civilian car ownership	191.4359	222.3085	258.1599	299.793

Table 3. Ownership of Civilian Car in Chongqing from 2013 to 2020 (Unit: million)

Year	2013	2014	2015	2016
Civilian car ownership	3.8552	4.53565	5.3361	6.2779
Year	2017	2018	2019	2020
Civilian car ownership	7.3859	8.6895	10.2231	12.0275

Then the civilian car ownership in China and in Chongqing from the year 2013 to 2020 is predicted, the results are shown in Table 2 and Table 3.

4.2. Forecast of the EV Ownership

According to the process to predict the EV ownership in a city, the EV ownership in the country should be calculated according to the planning EV ownership by cubic Hermite interpolation. Table IV shows the EV ownership in China from 2013 to 2020 according to the planning EV ownership 2.66 million and 16.98 million for the year 2015 and 2020 respectively. Then the EV ownership in Chongqing from the year 2013 to 2020 is predicted, the results are shown in Table 5.

Table 5. Ownership of EV in China from 2013 to 2020 (UNIT: MILLION)

Year	2013	2014	2015	2016
EV ownership	1.697	2.151	2.66	3.921
Year	2017	2018	2019	2020
EV ownership	6.373	9.626	13.292	16.98

Table 6. Ownership of EV in Chongqing from 2013 to 2020

Year	2013	2014	2015	2016
EV ownership	10200	19700	31100	55700
Year	2017	2018	2019	2020
EV ownership	83600	121500	154400	187400

5. Conclusion

A method based on BP neural network is presented in the paper to forecast the ownership of electric vehicle in a city. The input layer has seven neurons, which represents different economy factor influencing the ownership of electric vehicle. One hidden is designed in the model, which contains 3 neurons. Historical and statistical data of factors influencing the ownership of cars are collected in the past 20 years, which is the training sample for the BP neural network.

The forecast of the EV ownership of a city is based on that of a country at the initial stage for electric vehicles. The EV ownership in the city of Chongqing is predicted according the historical and statistical data from 1991 – 2010 and planning EV ownership in China, accuracy of the method is verified in this instance.

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Appendix- Statistical Data

The statistical data is from the website of National Bureau of Statics of China [12], the data from the year 1991 to 2010 was used, here we just list the data from the year 2001 to 2010.

Table A-1. GDP of China (unit: billion Yuan)

Year	2001	2002	2003	2004	2005
GDP	10806.82	11909.57	13517.40	15958.68	18361.85
Year	2006	2007	2008	2009	2010
GDP	21588.39	26641.10	31527.47	34140.15	40326.00

Table A-2. GDP of Chongqing (unit: billion Yuan)

Year	2001	2002	2003	2004	2005
GDP	197.686	223.286	255.572	303.458	346.772
Year	2006	2007	2008	2009	2010
GDP	390.723	467.613	579.366	653.001	792.558

Table A-3. Vehicle Production in China

Year	2001	2002	2003	2004	2005
Vehicle production	2341700	3251000	4443900	5074100	5704900
Year	2006	2007	2008	2009	2010
Vehicle production	7278900	8888900	9345500	13795300	18265300

Table A-4. Vehicle Production in Chongqing

Year	2001	2002	2003	2004	2005
Vehicle production	243800	331300	404500	428900	421500
Year	2006	2007	2008	2009	2010
Vehicle production	519900	708000	76.6400	1186500	1615800

Table A-5. Statistical Road passenger in China (unit: million)

Year	2001	2002	2003	2004	2005
Road passenger	14027.98	14752.57	14643.35	16245.26	16973.81
Year	2006	2007	2008	2009	2010
Road passenger	18604.87	20506.80	26821.14	27790.81	30527.38

Table A-6. Statistical Road passenger in Chongqing (unit: million)

Year	2001	2002	2003	2004	2005
Road passenger	592.44	619.18	582.90	634.95	604.36
Year	2006	2007	2008	2009	2010
Road passenger	612.28	771.87	1071.91	1145.98	1268.04

Table A-7. Per capita Crude Steel in China (unit: kg)

Year	2001	2002	2003	2004	2005
per capita crude steel production	119.22	142.43	172.57	218.28	270.95
Year	2006	2007	2008	2009	2010
per capita crude steel production	319.71	371.27	379.76	429.77	476.32

Table A-8. Per capita crude steel of Chongqing (unit: kg)

Year	2001	2002	2003	2004	2005
per capita crude steel production	59.8	63.9	75	92	93
Year	2006	2007	2008	2009	2010
per capita crude steel production	120	136	138	146	212

Table A-9.Per capita Generation Capacity in China (unit: kWh)

Year	2001	2002	2003	2004	2005
Per capita generation capacity	1164.29	1291.78	1482.91	1699.98	1917.79
Year	2006	2007	2008	2009	2010
Per capita generation capacity	2185.88	2490.01	2639.00	2790.08	3144.78

Table A-10. Per capita Generation Capacity in Chongqing (unit: kWh)

Year	2001	2002	2003	2004	2005
Per capita generation capacity	550.7	594.8	604	742	741
Year	2006	2007	2008	2009	2010
Per capita generation capacity	865	1095	1194	1307	1383