Forecasting the Number of Electric Vehicles: A Case of Beijing

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Abstract. Electric vehicles (EVs) have enjoyed fast-growing adoption in recent years, mainly thanks to the concern of climate change, environmental pollution, advancement of battery technology and expeditiously rising prices of crude oil. Rationally forecasting the number of EVs is quite important to their orderly development. This paper forecasts the number of EVs using the Bass diffusion model. Due to lack of sufficient historical data of EVs, analogy method is used to estimate the parameters of EVs according to the history diffusion data of private cars. The fuzzy analytic hierarchy process is used to calculate the weighted average of the main factors that influence users’ decisions of purchasing vehicles to estimate the parameters of Bass model.

1. Introduction

1.1. Background
In recent years, the energy crisis and environmental pollution are becoming more and more serious. The dramatically increase of the number of cars in a short period of time is the important cause of national large-scale ash haze weather appears. With the advantages of almost zero emissions and low pollution, electric vehicles (EVs) as an emerging vehicle technology have been long recognized as a promising way to reduce traffic emissions locally and petroleum dependence, with good prospects for development [1]. Therefore, rationally forecasting the number of EVs will be of great significance for adjusting the established industrial policy, realizing the orderly development of EVs, reasonably guiding the industrial layout of the upstream and downstream industry of EVs.

1.2. Literature review
EVs are currently seen by many countries as a way forward in the quest to decarbonise the private transport sector in the face of climate change, as over 10% of global greenhouse gas emissions come from road transport. Many studies have studied the diffusion of the alternative fuel vehicles (AFVs) [2, 3]. However, the studies specifically for EVs are relatively few. Shepherd et al. developed a system dynamics model of the UK take-up of EVs over the next 40 years considering the impact on uptake and CO2 emissions of factors such as subsidies, range, charge point availability, emission rates and a revenue preserving tax [4]. Becker et al. estimated the rate of market adoption of EVs in the United States through 2030 and analysed the impact of EVs deployment on the trade balance, business investment, employment, health care costs, and GHG emissions [5]. Glerum et al. presented a
comprehensive methodology that aims to evaluate the demand for EVs, and their paper contributed to the achievement of an operational model by three aspects, i.e., the survey design, the modelling framework, and the model application [6]. Xiong et al. presented a method to forecast the ownership of EVs based on the residual error gray model [7]. Ren et al. proposed an innovation diffusion model for EVs based on the extension of generalized Bass model considering infrastructure and price reduction effects [8].

The most widely used model to forecast the demand of new products is the Bass diffusion model. It can describe the S-shape penetration curve of new products with meaningful parameters such as the innovation factor (i.e., external influence factor) and imitation factor (i.e., internal influence factor) [9]. The model takes into account the impact of both the internal and external factors on the diffusion of new products, and it can predict the degree of diffusion of new products more accurately. In this paper, the Bass model is used to forecast the number of the EVs.

2. Model description

2.1. Bass diffusion model

The Bass diffusion model is a very useful tool for forecasting the adoption (first purchase) of a new product for which no closely competing alternatives exist in the marketplace. The related symbols are as follows:

- \( p \): The coefficient of innovation (i.e., coefficient of external influence);
- \( q \): The coefficient of imitation (i.e., coefficient of internal influence);
- \( m \): Total number of ultimate adopters (the market potential);
- \( N(t) \): The cumulative number of adopters by time \( t \);
- \( n(t) \): The number of adopters at time \( t \).

Assuming that each adopter buys only one-unit new product and the market potential does not change over time, then

\[
N(t) = m\left[\frac{1 - e^{-pqt}}{1 + q e^{-(p+q)t}}\right], \quad (1)
\]

\[
n(t) = m\left[p(p + q)\frac{e^{-(p+q)t}}{[p + q e^{-(p+q)t}]^2}\right]. \quad (2)
\]

Therefore, it is needed to first estimate the parameters \( p \) and \( q \) in order to forecast the number of EVs using Bass diffusion model.

2.2. Parameter estimation method for Bass diffusion model of EVs

The development of EVs in China is still at an early stage without sufficient historical data. Thus, the estimate values of the coefficients of Bass model cannot be directly obtained from the spread of the time series data. Therefore, analogy method is used to estimate the parameters of EVs Bass model according to the history diffusion data of private car. Let

\[
p_e = p_c \times \frac{\omega_{pe}}{\omega_{pc}} \quad (3)
\]
\[ q_e = q_c \times \frac{\omega_{pe}}{\omega_{qe}} \]  

(4)

Where \( p_c \) is the coefficient of external influence of private car; \( p_e \) is the coefficient of external influence of EVs; \( \omega_{pe} \) is the weighted average of the external influence factors of private car; \( \omega_{qe} \) is the weighted average of the external influence factors of EVs; \( q_c \) is the coefficient of internal influence of private car; \( q_e \) is the coefficient of internal influence of EVs; \( \omega_{qe} \) is the weighted average of the internal influence factors of private car; \( \omega_{qe} \) is the weighted average of the internal influence factors of EVs.

3. Case study

3.1. Parameter estimation for private car

The private car ownership of Beijing from 1990 to 2015 is selected as the sample data as listed in Table 1. The market potential is assumed to be \( m = 500 \) (ten thousand). The SPSS software is used to formulate a nonlinear regression model to do the prediction. Then \( p_c = 0.001 \) and \( q_c = 0.304 \) can be obtained. Accordingly, \( R^2 = 0.995 \), which suggests that the goodness of fit reaches a satisfactory level. Then, let 1990 as \( t = 1 \), take these parameters into (1), the forecasted cumulative purchase number of private cars over the years can be obtained as listed in Table 1. The last column shows the estimated error between the forecasted value and actual value of the private cars. It can be seen that the mean error from 2006 to 2015 is about 3.7967%, which means a good fitting. Fig. 1 shows the comparative results of the actual value and the forecasted value of private cars. The predicted results suggest that the Bass model can relatively well predict the diffusion process of private cars.

| Year | Private car ownership (Ten thousand) | Forecasted value (Ten thousand) | Estimated error (%) |
|------|-------------------------------------|---------------------------------|---------------------|
| 1990 | 2.79                                | 0.583948364                    | 79.066995112        |
| 1991 | 3.49                                | 1.375970398                    | 60.63122067         |
| 1992 | 4.86                                | 2.441747145                    | 49.7582892          |
| 1993 | 6.69                                | 3.883030635                    | 41.95768856         |
| 1994 | 8.55                                | 5.82501644                     | 31.87115275         |
| 1995 | 12.76                               | 8.435388401                    | 33.89194043         |
| 1996 | 17.36                               | 11.9329146                     | 31.26201265         |
| 1997 | 29.76                               | 16.59894728                    | 44.22396747         |
| 1998 | 40.74                               | 22.78821449                    | 44.06427469         |
| 1999 | 44.74                               | 30.93570446                    | 30.85482685         |
| 2000 | 49.41                               | 41.55414027                    | 15.8933158          |
| 2001 | 62.41                               | 55.21378198                    | 11.53055282         |
| 2002 | 81.08                               | 72.49415554                    | 10.58934935         |
| 2003 | 107.09                              | 93.89823239                    | 12.31839351         |
| 2004 | 129.78                              | 119.7273379                    | 7.745925452         |
| 2005 | 154                                 | 149.9328155                    | 2.641028913         |
| 2006 | 181.04                              | 183.9859299                    | 1.627225961         |
| 2007 | 212.1                               | 220.8274818                    | 4.114795777         |
| 2008 | 248.35                              | 258.9512787                    | 4.268648785         |
| 2009 | 300.3                               | 296.6280992                    | 1.222744175         |
| 2010 | 374.4                               | 332.2077127                    | 11.26930749         |
| 2011 | 389.7                               | 364.3926894                    | 6.494049424         |
| 2012 | 407.5                               | 392.393565                     | 3.707004536         |
| 2013 | 426.5                               | 415.9410945                    | 2.475710544         |
| 2014 | 437.2                               | 435.1830729                    | 0.461328259         |
| 2015 | 440.3                               | 450.5420399                    | 2.32615032          |
Figure 1. The comparative results of the actual value and the forecasted value of private cars.

3.2. Forecasting the EVs ownership
The main factors that influence users’ decisions of purchasing the vehicles (i.e., the influence factors of the Bass model) are listed in Table 2. The analytic hierarchy process (AHP) is a systematic and effective multi-criterion decision-making method which includes both qualitative and quantitative techniques. Van Laarhoven introduced the fuzzy theory into AHP to reflect the uncertainty of the evaluation for the importance of different factors and proposed the fuzzy analytic hierarchy process (FAHP) [10]. In this paper, the FAHP is used to construct the fuzzy judgment matrix of the importance of the relationships between different factors and get the weight coefficients of the importance of different factors.

Table 2. The influence factors of the Bass diffusion model.

| External influence factors | Government supports       |
|----------------------------|---------------------------|
|                           | Suitable facility construction |
| Internal influence factors | Price                     |
|                           | Difficulty of getting the license number |
|                           | Usability                  |
|                           | Environmental protection and energy saving |

Compare the influence factors with each other and use the method of 0.1-0.9 measure (shows in Table 3) to get the fuzzy comparison matrix for EVs shown in Table 4.

Table 3. The illustration of the 0.1-0.9 measure.

| Measures | The relative importance of two elements |
|----------|----------------------------------------|
| 0.5      | The two elements are equally important |
| 0.6      | One element is moderately important than the other one |
| 0.7      | One element is strongly important than the other one |
| 0.8      | One element is very strongly important than the other one |
| 0.9      | One element is extremely important than the other one |
| 0.1      | Converse comparison: if the judgment is $r_{ij}$ compared element $a_i$ with element $a_j$, the judgment will be $r_{ji} = 1 - r_{ij}$ compared element $a_j$ with element $a_i$. |
| 0.2      |                                          |
| 0.3      |                                          |
| 0.4      |                                          |
Table 4. The fuzzy comparison matrix for EVs.

| Influence factor                        | Government support | Suitable facility construction | Price | Difficulty of getting the license number | Usability | Environmental protection and energy saving |
|-----------------------------------------|--------------------|-------------------------------|-------|------------------------------------------|-----------|---------------------------------------------|
| Government support                      | 0.5                | 0.6                           | 0.5   | 0.4                                      | 0.6       | 0.8                                         |
| Suitable facility construction          | 0.4                | 0.5                           | 0.4   | 0.4                                      | 0.5       | 0.6                                         |
| Price                                   | 0.5                | 0.6                           | 0.5   | 0.5                                      | 0.4       | 0.7                                         |
| Difficulty of getting the license number| 0.6                | 0.6                           | 0.5   | 0.5                                      | 0.6       | 0.8                                         |
| Usability                               | 0.4                | 0.5                           | 0.6   | 0.4                                      | 0.5       | 0.4                                         |
| Environmental protection and energy saving| 0.2              | 0.4                           | 0.3   | 0.2                                      | 0.6       | 0.5                                         |

The fuzzy consistent judgment matrix can be obtained. Then the weights of the influence factors for EVs can be got as shown in Table 5.

Table 5. The weights of each influence factor for EVs.

| Influence factor                        | Government support | Suitable facilities construction | Price | Difficulty of getting the license number | Usability | Environmental protection and energy saving |
|-----------------------------------------|--------------------|-------------------------------|-------|------------------------------------------|-----------|---------------------------------------------|
| Weight                                  | 0.1803             | 0.1611                        | 0.1743| 0.186                                    | 0.1611    | 0.1373                                      |

A questionnaire survey for the influence factors is carried on. Respondents are asked to respectively score the acceptance of every influence factors for the EVs and private car on a scale of 1-5. Then calculate the weighted average score shown in Table 6. For EVs, the government support is stronger and it is easy to get the license number. Thus, the scores of these factors are higher. There are not sufficient charging facilities, which lead to the low acceptance of this factor. For private cars, it is difficult to get the license number in Beijing, which leads to the low score. The shorter driving range leads to the low score of the usability for EVs. In addition, the EVs are almost zero emissions. This leads to the big difference of the scores for private cars and EVs. Using the weights of each influence factor obtained in Table 6 and the weighted average score for each factor here, we can get the $\omega_p$ and $\omega_q$ for private cars and EVs.

Table 6. The weighted average for private cars and EVs.

| Vehicle kinds   | score       | Government support | Suitable facilities construction | Price | Difficulty of getting the license number | Usability | Environmental protection and energy saving | $\omega_p$ | $\omega_q$ |
|-----------------|-------------|--------------------|---------------------------------|-------|------------------------------------------|-----------|---------------------------------------------|-----------|-----------|
| Private cars    | 2.0         | 4.6                | 3.9                             | 1.5   | 4.6                                      | 2.2       | 1.10166                                     | 2.00189   |
| Electric vehicles| 4.6         | 2.0                | 3.0                             | 4.8   | 3.0                                      | 4.7       | 1.15158                                     | 2.54431   |
Take these values into (3) and (4), then \( p_e = 0.001045 \), \( q_e = 0.38637 \) can be obtained. The market potential for EVs is assumed to be \( m = 400 \) (ten thousand). The forecasted year-by-year EVs ownership can be obtained as listed in Table 7.

| Year | 2011 | 2012 | 2013 | 2014 | 2015 |
|------|------|------|------|------|------|
| EVs ownership | 0.5099 | 1.2586 | 2.3566 | 3.9631 | 6.3062 |
| Year | 2016 | 2017 | 2018 | 2019 | 2020 |
| EVs ownership | 9.7080 | 14.6136 | 21.6199 | 31.4893 | 45.1254 |

4. Conclusion

This paper forecasts the number of EVs using the Bass diffusion model. Private car, as a similar product of EVs, is selected to do the parameter estimation. According to the relevant policy requirements and planning targets of the promotion and application for the national new energy vehicle, the demand for EVs in Beijing will be about 600,000 by 2020. It can be seen that in the early stage of development, the growth rate of the EVs has not reached the expected value of the government. To a certain extent, the shorter driving range and the insufficient charging infrastructures are the primary factors that restrict the development of EVs. Therefore, improving the vehicle performance and increasing the driving range should become the focus of the auto makers, while the planning and construction of the charging infrastructures should become one of the key issues for the government.

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