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MODEL-DRIVEN FORECASTING FOR THE NUMBER OF PRIVATE ELECTRIC VEHICLES CONSIDERING SOCIAL PROPAGANDA AND SUBSIDY POLICY

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ABSTRACT

Private electric vehicle ("PEV") is an environmentally friendly transportation for household, which should be further popularized in the future together with electric vehicle ("EV"). Aiming at the strategy on promoting PEV, the impact of social propaganda and subsidy policy is explored by applying Bass model to forecast the number of PEV, which is non-periodic and annual. Bass model is effective to deal with the network externalities by considering the maximum market potential, the innovation coefficient, the imitation coefficient, and the adjustment coefficient. Combining actual data of the number of EV from Annual Report of Guangzhou, China, we demonstrate that social propaganda and subsidy policy will respectively affect the increasement of PEV in the long and short term, which means proper strategy should be adopted by authority to popularize EV.

Keywords: Private electric vehicles, forecasting, Bass model

1. INTRODUCTION

The industry of vehicle contributes a lot to the national economy in recent years. However, with the growth of the industry, a series of social problems happened in terms of energy demand and environment pollution, and have become new challenge to the development of the industry. In this context, new energy vehicle ("NEV") should be popularized among people in the future [1]. As an important part of NEV, electric vehicle ("EV") may serve the purpose of replacing oil with electricity to meet energy demand and mitigate energy pollution. In fact, the number of EV has grown rapidly, which may bring new problems during its large-scale integration into the grid, but good interacting behavior between EV as a type of energy storage and grid may benefit to the energy consumer. Nowadays, EV can be divided into private EV ("PEV"), public EV and official EV [2]. Public EV can take the form of electric taxis and electric buses. And PEV is used for household, which is the important part of EV.

Considering that the statistical data of vehicle is usually annual, forecasting of the number of vehicles should be a long-term prediction, in which regression models such as linear regression, multiple regression and exponential regression are simple but effective in the long-term prediction. Besides, samples of EV is still incomplete in this context, which means the lack of data to apply machine learning or other models that needs lots of sample.

Recently, few researches on the forecasting of the number of EV have been launched specially. The applied models can be divided into discrete choice model [2], multi-agent model [3] and diffusion model. Discrete choice model and multi-agent model focus on individual consumers. And diffusion model focus on the dynamic evolution of the market share after the birth of new products from a macro perspective, which can be divided into Bass model, Gompertz model and logistic model [4]. For instance, in [5], authors compared the short-term accuracy of a proposed modified Bass model and Lotka-Volterra model. Reference [6] improved Bass model on the time-varying innovation coefficient, the spatial imitation coefficient, and the adjustment coefficient defined to represent subsidies policy. Considering above, we will forecast the number of PEV by an improved Bass model to find out the impact of social propaganda and subsidy policy and try to help authority popularize EV among people.

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2. METHODS

2.1 Bass model

Bass model is a type of non-parametric conditional likelihood model to forecast spread of new products and scale of consumers accurately by taking full accounts of the internal and external factors [7].

Considering the cost of PEV and traditional vehicles to represent the subsidies policy to the behavior of EV purchases, generalized Bass model in the discrete time domain can be expressed as [7]:

$$f(t+1) = (1-F(t))(p(t)+q \bullet F(t))x(t) \tag{1}$$

Where

t refers to sequence of time; p, q, x refer to innovation coefficient, imitation coefficient and adjustment coefficient, respectively; f refers to ratio of new consumers to potential consumers; F refers to ratio of accumulative consumers to total potential consumers.

2.2 Maximum market potential

Following the survey of global consumers' purchase intentions for EV, especially in China [8], assuming that the maximum market potential is 90% of the number of private vehicles, which is related to the number of total vehicles. To calculate the maximum market potential, we investigate actual number of private vehicles and total vehicles of Guangzhou, China from 2001 to 2018 [9]. Pearson correlation coefficient between the number of private vehicles and total vehicles is 0.9971. The number of private vehicles has reached 2.03 million as the baseline until 2018.

Different estimations are performed to find out different trends of private vehicles, which is non-periodic. Linear model and third-order polynomial model are the basis of linear estimation and third-order polynomial estimation, which is expressed as followed. As for stationary estimation, we assume the number of private vehicles from 2019 to 2025 will increase as before, especially from 2010 to 2015.

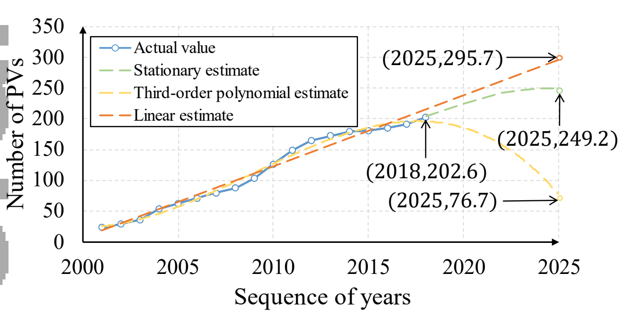

Figure 1: Trend diagram of number of private vehicles

$$y_L(t) = ax(t) + b \tag{2}$$

$$y_P(t) = cx^3(t) + dx^2(t) + ex(t) + f \tag{3}$$

Where

$y_L(t)$ refers to linear estimation; $y_P(t)$ refers to third-order polynomial estimation; $a, b, c, d, e, \mathrm{f}$ relatively refer to constant coefficients of linear model and third-order polynomial model, which are usually estimated by least squares estimation.

So far, different trends (2019-2025) of the number of private vehicles have been forecasted through stationary estimation, third-order polynomial estimation and linear estimation as Figure 1. Stationary trend means the number of private vehicles increases rapidly in the short term. Linear trend means the number of private vehicles increases rapidly in the long term. Polynomial trend means the number of private vehicles decreases in the long term.

2.3 Innovation coefficient and imitation coefficient

Innovation coefficient represents external influence and means consumers purchase some type of new product spontaneously because of social propaganda like advertisement in life. Innovation coefficient is between 0 and 1. The closer innovation coefficient to 1, the easier it is for these customers to accept EV. Compared with other durable goods, innovation coefficient is usually between 0.01 and 0.03 [11], which is based on experience. Besides, imitation coefficient represents internal influence and means other consumers purchase some type of product after knowing its convenience, reliability, durability from consumers who have already purchased or other network externalities. Still, innovation coefficient is between 0 and 1. The closer imitation coefficient to 1, the easier it is for EV to diffuse among potential customers. Compared with other durable goods, innovation coefficient is usually between 0.3 and 0.7 [11], which is also based on experience.

We set imitation coefficient as constant and further model innovation coefficient considering advertisement and people's acceptance of advertising as [10]:

$$p(t) = p(t-1) + \varphi_M M \tag{4}$$

Where

φ_M refers to people's acceptance of advertising; M refers to advertisement; $p(0)$ is set to be 0.01.

2.4 *Adjustment coefficient*

Adjustment coefficient represents subsidies policy to the behavior of EV purchase. Still, adjustment coefficient is further modelled by purchase cost and usage cost of common vehicles and EV as [11]:

$$x(t) = 1 + \beta \frac{C_{EV}(t) - C_{CV}(t)}{C_{CV}(t)} \tag{5}$$

$$C_{buy}(t) = \left(1 - \left(\frac{1 - r_{dep}}{1 + \gamma}\right)\right) C_p(t) - C_s(t) \tag{6}$$

$$C_{opt}(t) = \sum_{k=t}^{t+\tau} \frac{P(k) d_{annual} + C_m}{(1+\gamma)^{k-t}} \tag{7}$$

Where

β refers to the cost influence coefficient, which is set as constant; C refers to total cost, which is the sum of C_{buy} and C_{opt}; C_{EV} refers to total cost of EV; C_{CV} refers to total cost of common vehicles; C_{buy} refers to purchase cost that is different for common vehicles and variable for EV; C_{opt} refers to usage cost; C_p refers to sales price of vehicles including tax, which is relatively constant for common vehicles and variable for EV; C_s refers to amount of subsidies for EV purchases; $r_{dep}, \gamma, d_{annual}, \tau, C_m$ refer to constants of depreciation rate of vehicles, discount rate, annual driving distance of vehicles, estimated service life of vehicles and annual maintenance cost of EV and common vehicles; P refers to energy cost per unit mileage of vehicles, which is different for EV and variable for common vehicles.

Besides, assuming that C_{buy} of EV decreased 8% every year for EV and $C_{buy}(2018)$ is 200000, and P of common vehicles increased 3% for common vehicles and $P(2018)$ is 49 [6]. And constants and their values are listed as Table 1.

2.5 *Forecasting of number of PEV*

The number of PEV is assumed to reach 0.118 million until 2018 because the number of EV has reached 0.15 million until 2018 [12] and private vehicles accounts for 78.74% of total vehicles in 2018. We assume (1) behavior of repeated purchase doesn't exist; (2) supporting facilities and maintenance services of EV are basically complete; (3) implement subsidies of PEV continues in the near future; (4) electric power system operates normally when large scale of EV are connected to grid.

Table 1: Constants of Bass model and their values

Constant	Value	Unit
q	0.5	-
φ_M	0.004	-
β	-2.4	-
r_{dep}	20%	-
γ	6%	-
d_{annual}	8000	km
τ	12	year
C_p of common vehicles	108500	￥
P of EV	27	￥
C_m of common vehicles	3000	￥
C_m of EV	2500	￥

Figure 2 shows forecasting of number for PEV in different M with the unit of ten thousand, assuming the subsidy decreased 20% every year and the trend of private vehicles is forecasted by linear estimation. In the short term, the inventories of PEV are close. But as time goes on, effect of advertisement will be more obvious. The inventories of PEV in $M = 0.2$ and $M = 1$ are relatively 16.5 and 17.7 in 2025.

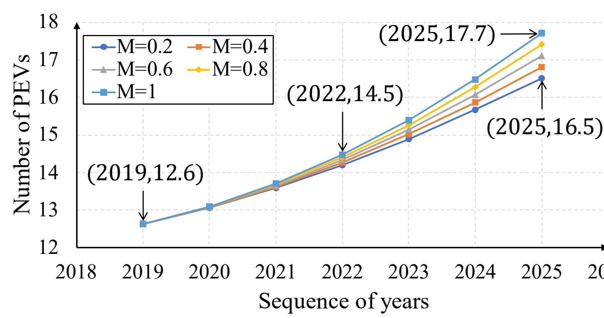

Figure 2: Forecasting diagram of number of PEV in M

Figure 3 shows forecasting of number for PEV in different subsidies with the unit of ten thousand, assuming the trend of private vehicles is forecasted by linear estimation and $M = 0.6$. In the context, the price of PEV is much more expensive than that of common

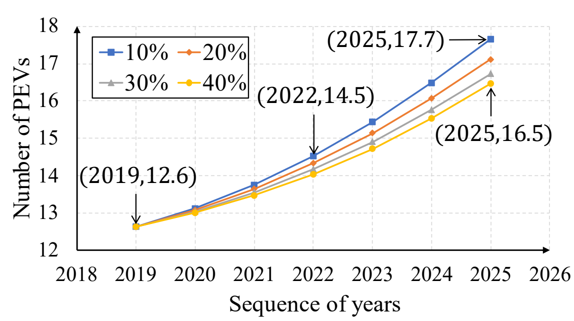

Figure 3: Forecasting diagram of number of PEV in subsidies

vehicles. The degree of subsidies for the behavior of EV purchases will influence the number of PEV earlier than that of M . The inventories of PEV in 10% and 40% decreased subsidies are relatively 17.7 and 16.5 in 2025.

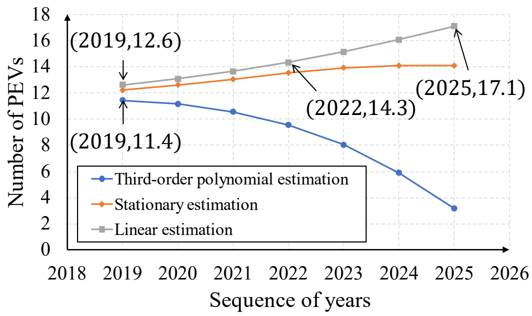

Figure 4: Forecasting diagram of number of PEV in trends

Figure 4 shows forecasting of number for PEV in different trends of the number of private vehicles with the unit of ten thousand, assuming $M=0.6$ and the subsidy decreased 20% every year. The inventories of PEV differ even in the short term. And as time goes on, the effect of different trends will influence the number of PEV in positive and negative way. Combined with the policy in China, the linear trend is more reliable.

Assuming that the number of private vehicles will continue to grow, the linear trend is used to discuss the impact of advertisement, which represents social propaganda, and subsidy to the diffusion of PEV in the market. Unlike discrete choice model and multi-agent model, all the predicted results from improved Bass model dynamically show that PEV market will continue to grow exponentially and EV will not be saturated in the next 10 years. It is clear that the industry will develop in different way when government tends to subsidy policy or social propaganda, which means proper policy should be established to develop the industry of EVs properly.

3. CONCLUSIONS

This paper proposes an improved Bass model and discusses the impact of subsidy policy and social propaganda to the popularization of PEV by forecasting the number of PEV. Specifically, we focus on the dynamic evolution of PEV in the market and make Bass model more suitable to the forecasting in this study by making some different estimations on the trends of private vehicles, and further modelling the general Bass model with innovation coefficient and adjustment coefficient. We hope that our work may help authority to develop the industry of EV properly. Actually, we may improve the model further again by considering supply or repeated purchases. Besides, we will apply Bass model to other cities to verify its universality.

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REFERENCE

[1] IEA. Global EV Outlook 2020. Paris: IEA; 2020.

[2] Train KE, Winston C. Vehicle choice behavior and the declining market share of US automakers. International Economic Review 2010;48:1469-1496.doi:10.1111/j.1468-2354.2007.00471.x.

[3] Shafiei E, Thorkelsson H, et al. An agent-based modeling approach to predict the evolution of market share of electric vehicles: A case study from Iceland. Technological Forecasting & Social Change 2012;79:1638-1653. doi:10.1016/j.techfore.2012.05.011.

[4] Trappey CV, Wu HY. An evaluation of the time-varying extended logistic, simple logistic, and Gompertz models for forecasting short product lifecycles. Advanced Engineering Informatics 2008;22:421-430. doi:10.1016/j.aei.2008.05.007.

[5] Li S, Chen H, Zhang G. Comparison of the Short-Term Forecasting Accuracy on Battery Electric Vehicle between Modified Bass and Lotka-Volterra Model: A Case Study of China. Journal of Advanced Transportation 2017;2017:1-6. doi:10.1155/2017/7801837.

[6] Yu H, Zhang Y, Pan A. Medium- and Long- term Evolution Model of Charging Load for Private Electric Vehicle. Automation of Electric Power Systems 2019;43:80-87. doi:10.7500/AEPS20190221003.

[7] Bass FM, Krishnan TV, Jain DC. Why the Bass model fits without decision variables. Marketing Science 1994;13:203-223. doi:10.1287/mksc.13.3.203.

[8] Giffi C. Survey of global consumers' purchase intentions for electric vehicles. London: Deloitte Touche Tohmatsu Limited; 2011.

[9] Guangzhou Statisitcs Bureau. Guangzhou Statistical Yearbook. Beijing: China Statistics Press; 2000-2019.

[10] Eppstein MJ, Grover DK, Marshall JS, et al. An agent-based model to study market penetration of plug-in hybrid electric vehicles. Energy Policy 2011;39:3789-3802. doi:10.1016/j.enpol.2011.04.007.

[11] Long Z, Chang J, Chen Z. Effects of incentives to the promotion of new energy vehicles-based on the empirical analysis of modified Bass model. Science and Technology Mangement Research 2016;34:138-144. doi:10.3969/j.issn.1000-7695.2016.04.026.

[12] Guangzhou Academy of Social Sciences. Annual Report on Guangzhou Automobile Industry (2019). Beijing: Social Science Literature Press; 2019.