Reviews on Market Forecasting Modeling Study for New Energy Vehicle

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Abstract
The Discrete Choice Model, Innovative Product Diffusion Model and Agent Based Model are three principal models in the field of market forecasting modeling study for New Energy Vehicle, each model has distinctive characteristics of their basic assumptions, model bases, parameter selection and application scenarios. Short data time-span, lack of nationwide consumer data and strong policy implication are striking features in respect of NEV market analysis of China. One of the key preconditions to accept or use forecasting results for judgment is to admit the limitation of forecasting based on which we can select model parameters and build models for the purpose of the research.

Key words: New Energy Vehicles; Market Forecasting; model; theory

1. INTRODUCTION

With rapid growth of automotive industry and car stock, pollution and energy pressure are presenting themselves as problems more severe than ever, which also cause big challenges to automotive development in China. Within the new environment of energy safety and environmental protection, NEV has been chosen by China as a key strategy to develop automotive industry.

Since “863” EV project launched in 2001, China has released a successive series of policies to support the R&D and industrialization of NEV. From 2011 to 2016, 597,700 NEVs have been sold in China, making it the biggest NEV market in the world with its share in global new-energy passenger vehicles rising from 4.29% in 2011 to 47.97% in 2016. The industry of NEV is taking shape in China, which provides a huge base of data for future development.

China’s government has announced its plan, target and direction of automotive development in documents including Energy-saving and New-energy Vehicle Industry Development Plan (2012-2020) and Made in China 2025. Within this framework, it's essential to understand market trends, implement policies and achieve targets in the planning and management of automotive market. Relevant influencers should be identified and appropriate methods should be employed to make reasonable forecasting of NEV development.

In terms of NEV market forecasting, many home and abroad researches have made progresses. Some research projects are based on certain models or methodology or limited to some types of markets, which led to scenario-restricted judgment of NEV market. Those projects, however, leave us wonder about the fundamentals, indications, criteria and applicable scopes of various forecasting models. No studies have been made to put these forecasting models together and to draw generalized conclusions, leading to the current lack of systematic and comprehensive knowledge about NEV market forecasting.

This study will provide a comprehensive description of the models and methodology of NEV market forecasting used by home and abroad researchers, with expectation to get generalized knowledge about NEV market forecasting by clarifying the following questions. 1. Which models were used in previous researches and what features do they possess? 2. How are mostly used models structured? What influencers and methods are adopted and what results were achieved? 3. How well are we prepared to develop a market forecasting model for China and what challenges are we facing?

2. GENERAL FEATURES OF NEV MARKET FORECASTING MODELS

As an emerging sector closely watched or supported by major countries and companies, NEV is being studied by many projects to explore its growth trend and rate. These forecasting studies bear different concepts.

¹China’s market data comes from CATARC-ADC and foreign market data from marklines
²According to Energy-saving and New-energy Vehicle Industry Development Plan (2012-2020) (No.22 Document of the State Council[2012]), by 2020, China should have the capacity of producing 2 million BEVs and PHEVs and have produced and sold over 5 million BEVs and PHEVs accumulatively; According to Made in China 2025 Technology Roadmaps for Key Fields, by 2020, the annual sales of domestic NEV should reach 1 million vehicles, taking over 70% of market share; by 2025, 3 million domestic NEVs with internationally advanced technologies should be sold annually, representing over 80% of market share.
and goals (policy makers use studies to assess the impacts of policies, manufacturers want to grab market trends and researchers assess consumer choices), incorporate various fields of science and focus on different aspects (policy, economy and business).

15 home and abroad articles about NEV market forecasting were selected (Table 1) in this study, covering China, U.S. Germany, the Netherland, Iceland and Korea. The Discrete Choice Model, Innovative Product Diffusion Model (mainly BASS model) and Agent Based Model are the most frequently used models which will be thoroughly explored in the following chapters.

<table>
<thead>
<tr>
<th>NO.</th>
<th>Author</th>
<th>Model adopted</th>
<th>Base model</th>
<th>Applicable market</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Thomas A. Becker</td>
<td>No</td>
<td>BASS model</td>
<td>NEV, U.S.</td>
</tr>
<tr>
<td>2</td>
<td>J. L. Sullivan et al.</td>
<td>VAMMP Model</td>
<td>Agent based model</td>
<td>PHEV, U.S.</td>
</tr>
<tr>
<td>3</td>
<td>Bernd Propfe et al.</td>
<td>VECTOR21 Model</td>
<td>Multivariable linear regression model</td>
<td>New-energy passenger vehicle, Germany</td>
</tr>
<tr>
<td>4</td>
<td>Zhaoyang Duan et al.</td>
<td>No</td>
<td>Agent based model</td>
<td>NEV, U.S.</td>
</tr>
<tr>
<td>5</td>
<td>Till Gnann et al.</td>
<td>ALADIN Model</td>
<td>Stock model</td>
<td>NEV, Germany</td>
</tr>
<tr>
<td>6</td>
<td>Susanne Linder and Johannes Wirges</td>
<td>No</td>
<td>BASS model</td>
<td>NEV, Stuttgart, Germany</td>
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<tr>
<td>7</td>
<td>Xinyu Cao</td>
<td>No</td>
<td>BASS model</td>
<td>New-energy passenger vehicle, Germany</td>
</tr>
<tr>
<td>8</td>
<td>Argonne National Laboratory</td>
<td>LVChoice Model</td>
<td>Discrete Choice Model</td>
<td>NEV, U.S.</td>
</tr>
<tr>
<td>9</td>
<td>Oak Ridge National Laboratory</td>
<td>MA3T Model</td>
<td>Discrete Choice Model</td>
<td>New-energy passenger vehicle, U.S.</td>
</tr>
<tr>
<td>10</td>
<td>Shijun Fu and Yulong Ren</td>
<td>No</td>
<td>Dual group evolutionary model</td>
<td>NEV, China</td>
</tr>
<tr>
<td>11</td>
<td>Yongseung Lee et al.</td>
<td>No</td>
<td>Discrete Choice Model</td>
<td>Hybrid, Korea</td>
</tr>
<tr>
<td>12</td>
<td>Ehsan Shafiei et al.</td>
<td>No</td>
<td>Agent based model</td>
<td>NEV, Iceland</td>
</tr>
<tr>
<td>13</td>
<td>Ayla Kangur et al.</td>
<td>STECCAR model</td>
<td>Agent based model</td>
<td>NEV, Netherland</td>
</tr>
<tr>
<td>14</td>
<td>Ziquan Long et al.</td>
<td>No</td>
<td>BASS model</td>
<td>NEV, China</td>
</tr>
<tr>
<td>15</td>
<td>Jun Ma et al.</td>
<td>No</td>
<td>AHP and Logit regression</td>
<td>NEV, China</td>
</tr>
</tbody>
</table>

Influencers are the fundamental building blocks of any model. The researchers of these projects built their forecasting algorithms based on the characteristics of their models and the influencers of NEV market carefully selected. A statistics of the independent variables of these 15 models showed the frequency of influencers adopted, as shown in Chart 1. Factors of “expense” such as energy price, vehicle purchase price, financial and tax incentive and driving range which have indirect impact on usage cost are mostly used influencers when researchers build their forecasting models. Factors of “usage” such as vehicle performance and infrastructure convenience are also important. This indicates that factors influencing consumers’ economic utility and usage convenience are considered most when building a forecasting model.

![Figure 1. Frequency of influencers adopted in models](chart1.jpg)
All the 15 models predict the stock and market share of NEV in future years. However, considering how different these countries are from each other, it’s hard to determine the absolute amount of NEV in future, based on the forecasting results. Therefore, we chose the forecasts of NEV market share in different regions for comparison, and the result is shown in Chart 2. Because the models covered and analyzed different scenarios (e.g. different gas prices and tax policies), we only chose the results from basic scenarios (based on current development trend which will not change). As shown in the chart, all studies are positive about the future of NEV based on predictions of rising market shares year by year.

Figure 2. Forecasts of NEV market share by the models

3. MAIN MODELS USED IN NEV MARKET FORECASTING

(1) Discrete Choice Model

Discrete Choice Model is a widely adopted method in transportation research to describe the transport option decision of individuals or groups. It calculates the probability of consumers choosing products or solutions influenced by their preference. Since the dependent variables of product or solution selection (e.g. brand and technology type) are discrete variables, there is limitation on the linear regression model conventionally used to study continuous variables. Under this circumstance, Discrete Choice Model provides an optimal analysis option.

As for NEV market forecasting, by taking consumers’ transport option, vehicle technology, vehicle performance and economy into consideration, Discrete Choice Model study how consumers with different preferences make choice when they buy and possess different types of vehicles. That’s why the model can be used to study the market distribution of various vehicle types in future.

As for the structure of model, Discrete Choice Model often generates Choice Sets comprising a certain amount of products or solutions, with each set containing the attributes, characteristics or levels of the product or solution. Consumers choose one set from sets with different attributes, characteristics and levels, based on certain rules.

The process of choice shows that Discrete Choice Model is built on 2 assumptions.

i. All Choice Sets are mutually exclusive with no overlaps. For example, if we have built 4 Choice Sets – “bus”, “subway”, “car” and “walk” and then we want to study “first walk then subway” scenario, we need to rebuild Choice Sets by establishing 5 sets – “bus”, “subway”, “car”, “walk” and “first walk then subway”, to make sure they are mutually exclusive.

ii. Consumers make rational choices. In real life, decisions vary from person to person and both rational and random choices exist. In model calculation, however, random choices cannot be used as dependent variables, which have impacts on decision-making, so it cannot forecast choice behavior under certain conditions. To make sure the logic is reasonable, Discrete Choice Model assumes that consumers make rational choices based certain rules, for example maximized utility, etc.

In terms of NEV market research, Discrete Choice Model conducts statistical analysis based on discrete, non-linear Multinomial Logit Model and utility theory, which has a basic formula shown as:

$$P(i|\mathcal{C}_n) = \frac{e^{\mu V_{in}}}{\sum_{j \in \mathcal{C}_n} e^{\mu V_{jn}}}$$

$\mathcal{C}_n$ means n Choice Sets; i means the product or solution of final choice; $\mu$ is the elastic coefficient of
each Choice Set; \( V_{in} \) means the utility of choosing \( i \).

In the first step, for example, we can divide passenger vehicles into sedan, SUV and MPV (level 1); each category can be further divided by technology type, e.g. fossil-fuel, hybrid or new-energy sedan (or SUV, MPV) (level 2); therefore all passenger vehicles available in the market can be distributed into 9 Choice Sets in 2 levels\(^2\).

According to the settings of Choice Set, the probability of choosing new-energy sedan (NES) is:

\[
P(\text{NES}) = P(\text{NES}|\text{sedan}) \times P(\text{sedan}|\text{car})
\]

According to the basic formula of Discrete Choice Model, we have:

\[
P(\text{NES}|\text{sedan}) = \frac{e^{\mu_{\text{sedan}} V_{\text{NES}}}}{e^{\mu_{\text{sedan}} V_{\text{NES}}} + e^{\mu_{\text{sedan}} V_{\text{FFS}}} + e^{\mu_{\text{sedan}} V_{\text{HS}}}}
\]

\[
P(\text{sedan}|\text{car}) = \frac{e^{\mu_{\text{car}} I_{\text{sedan}}}}{e^{\mu_{\text{car}} I_{\text{sedan}}} + e^{\mu_{\text{car}} I_{\text{SUV}}} + e^{\mu_{\text{car}} I_{\text{MPV}}}}
\]

\( I_{\text{sedan}} \) is intrinsic value, which is expressed by the following formula:

\[
I_{\text{sedan}} = \frac{1}{\mu_{\text{sedan}}} \ln \left( e^{\mu_{\text{sedan}} V_{\text{NES}}} + e^{\mu_{\text{sedan}} V_{\text{FFS}}} + e^{\mu_{\text{sedan}} V_{\text{HS}}} \right)
\]

\( V_{\text{NES}} \) can be understood as the utility generated by usage of NEV, expressed by the following formula:

\[
V_{\text{NES}} = \beta_1 A_1 + \beta_2 A_2 + \beta_3 A_3 + \ldots
\]

Note: NES=new-energy sedan, FFS=fossil fuel sedan, HS=hybrid sedan

\( A_n \) is the utility value of each attribute, e.g. vehicle sales price, subsidy, purchase tax, repair cost, fuel cost, electricity cost, and \( \beta_n \) is the coefficient of this value.

In this way, we have built a Discrete Choice Model based on 9 Choice Sets. It’s worth noting that the sums of conditional probabilities in both levels are 1.

\[
P(\text{NES}|\text{sedan}) + P(\text{FFS}|\text{sedan}) + P(\text{HS}|\text{sedan}) = 1
\]

\[
P(\text{sedan}|\text{vehicle}) + P(\text{FFS}|\text{vehicle}) + P(\text{HS}|\text{vehicle}) = 1
\]

(2) Innovative Product Diffusion Model

The degree of market penetration is one of the measures that indicate the diffusion of a product, usually expressed by rate of diffusion. Product diffusion models built with rate of diffusion and time series are frequently used in the research of market diffusion of emerging products such as TV, the Internet and mobile phone. Innovative Product Model believes that the market penetration of a new product is a process: early adopters know about and use the product, and then word of mouth contributes to the diffusion of product information which finally expands to all user groups. The Bass model invented by Frank M. Bass, a leading market research expert, and its extended versions are among the most used models for studying the diffusion of innovative products.

When discussing the extended applications of Bass model, Frank Bass proposed 9 basic assumptions, which can be put into the 3 following categories:

i. the market diffusion of an emerging product happens in a non-competitive environment, which means the diffusion is not effected by product competition. The amount and quality of supply is also free from restrictions.

ii. the environment where the new emerging product diffuses remains unchanged, which means as time passes, the performance attributes, max. Market potential and market boundary remain unchanged during the process of diffusion.

iii. Inspired by the research of Everett Rogers\(^1\). Bass model believes that the diffusion of emerging product is affected by two factors: external and internal influences. External influences work when easily recognized product traits (like price, external design, size, etc.) are promoted and spread, and the consumers influenced by these traits are called innovators; internal influences work when word-of-mouth transfer from consumers to consumers.

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\(^1\)The classification presented here is simplified for the purpose of clarification, but it can be much more refined based on the requirements of study. For example, BEV can be further divided by driving range.

\(^2\) Everett Rogers believes that there are five types of potential consumers of emerging products. The first 2.5% adopters are innovative consumers, the following 13.5% early consumers, the next 34% early major consumers, the next 34% late major consumers, and the last 16% lag-behinds. See Rogers, E. M., The Diffusion of Innovation, Third Ed., Free Press, New York, 1983. Frank Bass believes that besides the first group, other four groups are influenced by social media and existing consumers, so he defines the first group as innovators and the following groups as imitators.
potential consumers, and these consumer groups are called imitators.

Based on this assumption, Bass Model has the following basic formula:

\[ \frac{dF(t)}{dt} = p[m - F(t)] + q \frac{F(t)}{m} [m - F(t)] \]

In terms of NEV market analysis, \( F(t) \) can be understood as accumulative NEV consumption at time \( t \); \( m \) means the maximum market potential of NEV; \( p \) is coefficient of external influence which represents the growth speed of innovators (value 0-1, the closer the value is to 1, the faster the innovators buy NEV); \( q \) is coefficient of internal influence which represents the growth speed of imitators (value 0-1, the closer the value is to 1, the faster the imitators buy NEV).

If we solve the differential equation of Bass Model, we can get its curvilinear equation:

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

As shown in the equation, if we use historical data to solve the values of \( m, p \) and \( q \), we can use them to calculate the accumulative NEV consumption at a future time \( t \).

However the equation only depends on accumulative historical data but ignores key factors including NEV performance and usage cost. To address this flaw, the extended Bass model incorporates a coefficient of decision-making \( x \), representing relevant factors influencing decision-making of consumption. This effort expanded the scope of model factors. Some studies defined \( x \) as cost advantage of NEV over conventional vehicle, so they put purchase price, usage price and energy price into models for analysis.

(3) Agent based model

Agent based model is a calculation method based on computer emulation analysis. By setting property factors of the relevant Agent in the study, such as their value preference, natural talent, behavior pattern, the model can make them interact with each other in relevant environments and simulate their evolution under different scenarios over time. This is a from-bottom-to-top analysis method by allowing the interaction of microscopic subjects to form macroscopic impacts.

Compared with other models, which focus more on influencers of “object” such as product quantity and attributes, Agent based model shows more effects of “human”. In the early stage of building an Agent based model for NEV market forecasting, the behavioral agent, or Agent, should be established, such as consumer, automaker, policy maker, energy or infrastructure provider, whose attributes should also be defined.

The “consumer” Agent contains both attributes relevant to vehicle demands and their own properties. Attributes of vehicle demands include vehicle type, technology type, product performance, and cost, etc. Consumer properties include gender, age, income, region, driving range, etc. Agent based model can assess consumers’ purchase behavior based on their demands and preferences.

The “automaker” Agent contains attributes relevant to vehicle supply, such as vehicle type, technology type and product performance, which correspond to the demands of consumers. Automakers carry out production behavior by balancing policies and regulations, consumption demands and incentives for production, etc.

Similarly, policy makers and infrastructure providers’ behaviors are based on their own attributes and rules. Agent based model achieves a balance by allowing Agents to interact, learn and adapt with each other under certain rules. Table 2 shows the process of building an Agent based model.

Table 2. Steps of building an Agent Based Model

<table>
<thead>
<tr>
<th>1. Define subject</th>
<th>Consumer</th>
<th>Automaker</th>
<th>Policy maker</th>
<th>Infrastructure supplier</th>
</tr>
</thead>
<tbody>
<tr>
<td>2. Define attributes of subject</td>
<td>Individual properties (gender, income, demand for range)</td>
<td>Supply (type, performance and cost, etc.)</td>
<td>Policy (design mechanism, purchase incentive, fine, etc.)</td>
<td>(Energy price, quantity of infrastructure, etc.)</td>
</tr>
<tr>
<td>3. Define rule of behavior</td>
<td>Meet driving range requirement, minimize cost within income range, etc.</td>
<td>Maximize profit, maximize market share, etc.</td>
<td>Reduce energy consumption and pollution, etc.</td>
<td>Maximize profit, maximize market share, etc.</td>
</tr>
</tbody>
</table>

4. Simulate with computer

(4) Comparison of main models

Generally, 3 models for NEV market forecasting vary from each other on model principal, data demands
and applicable scenarios. By comparing their data features, model applications, outputs and model complexity, we got the results shown in Table 3.

Discrete Choice Model is a model based on the assumption that consumers make rational choices, the purpose of which is to study the market distribution of different types of vehicles. As for influencers and parameters calculation, Discrete Choice Model, which is based on the theory of utility maximization, incorporate different utilities that may be exerted on consumers when they choose different vehicles, so consumers’ daily driving behaviors (driving range, charging time, convenience of energy access, etc.) are taken as model factors. It also calculates the elastic coefficient $\mu$ for each selected level based on historical data. Therefore Discrete Choice Model is built based on a certain amount of consumer survey data. Its output is the sales volume of various vehicle types at time $t$ (the amount of types is determined by the amount of Choice Sets).

Innovative Product Diffusion Model is a model that estimates future data based on historical data, the purpose of which is to study the development of NEV market volume under certain market potential. Bass Model requires the easiest way, among the three models, to build parameters. Conventional Bass model only uses historical NEV sales or stock data and influential parameter of market potential to estimate the value of $m$, $p$ and $q$ in the model. The extended Bass model incorporates influencers like price, cost and infrastructure but generally ignores the attitudes of consumers, so it’s easy to build parameters. The output of Bass model is the sales volume or stock of NEV at time $t$.

Agent based model is a computational emulation and analysis method based on preset attributes and behaviors of study subjects, the purpose of which is to analyze the future evolution of NEV market driven by the interaction of different stakeholders. It requires presetting the attributes and behavioral rules of study subjects when building an Agent based model. In addition, because it’s a computational emulation and analysis method, it also requires the ability to realize mathematical models using multiple programming and UML, besides parameter choice and data system structuring. Therefore it’s the most difficult model to achieve among the 3 mentioned models.

<table>
<thead>
<tr>
<th>Table 3. Comparison of 3 major models for NEV market forecasting</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Model</strong></td>
</tr>
<tr>
<td><strong>Purpose</strong></td>
</tr>
<tr>
<td><strong>Data and parameters</strong></td>
</tr>
<tr>
<td><strong>Output</strong></td>
</tr>
<tr>
<td><strong>Computational complexity</strong></td>
</tr>
</tbody>
</table>

4. THREE TOP CHALLENGES TO THE FORECASTING OF CHINA NEV MARKET

After comparing mainstream models for NEV market forecasting as well as their methodology and characteristics, we also need to ask this question: what’s special about China’s market and what challenges or restrictions does this specialty cause on its forecasting? The effort to solve this issue is also the one to find out which models are more applicable to us in the current period. In general, we are presented with 3 big challenges when we try to carry out forecasting for NEV market in China.

(1) **Time span of data is short**

As a quantitative analysis method to forecast future based on existing data, time series analysis is widely applied in statistics. Its basic principle is to present continuous characteristics with a certain pattern in the
process of an object’s development, allow these continuous characteristics to develop by original patterns under certain circumstances by controlling the influencers which may change the object, so that future forecasting is achieved based on current patterns. All existing mainstream models use historical data of a certain time span for parameter estimation or trend deduction.

This continuity of time series analysis poses certain demands for the time span of continuous data. The longer the time span of original data is, the more evidence we get to reflect the law of development of an object, and the more accurate the forecasting result is, theoretically.

Comparison of articles home and abroad about NEV market forecasting shows that studies abroad use data of longer time spans which usually go beyond 15 years, thanks to their long history in market forecasting and statistical efforts in early years.

The work of statistics in relevant fields started late in China. Authorities can only provide complete data about energy price starting from 2000, and fossil-fuel car data from 2004. The gross volume of NEVs is not small, but complete data about NEV sales volume only starts from 2011 due to short development. Compared with statistical data of automotive and energy industry accumulated in dozens of years, the time span of China’s historical data is short. However as time passes and NEV develops fast, the data used in modeling will become more and more comprehensive.

Table 4. Time spans of the historical data of some factors in articles home and abroad about NEV market forecasting

<table>
<thead>
<tr>
<th>Author</th>
<th>Model factor</th>
<th>Time span</th>
</tr>
</thead>
<tbody>
<tr>
<td>Thomas A. Becker</td>
<td>Oil resources in U.S.</td>
<td>(1981-2009) 29 years</td>
</tr>
<tr>
<td>Zhao Yang Duan et al.</td>
<td>Driving range</td>
<td>(1980-2009) 30 years</td>
</tr>
<tr>
<td>Yongseung Lee</td>
<td>Typical HEV market distribution</td>
<td>(1999-2009) 21 years</td>
</tr>
<tr>
<td>Till Gnann et al.</td>
<td>Ratio of repurchasing HEV</td>
<td>(2003-2012) 10 years</td>
</tr>
<tr>
<td>Shijun Fu et al.</td>
<td>Family trip in Germany</td>
<td>(1994-2010) 17 years</td>
</tr>
<tr>
<td>Yingqi Liu et al.</td>
<td>Stock of gasoline vehicle in China</td>
<td>(1990-2007) 18 years</td>
</tr>
<tr>
<td>Fang Dong et al.</td>
<td>Global sales volume of an HEV model</td>
<td>(1997-2011) 15 years</td>
</tr>
<tr>
<td></td>
<td>7 factors including total output value of automotive industry</td>
<td>(2010-2014) 5 years</td>
</tr>
</tbody>
</table>

(2) Country-level consumer data is insufficient

All three models for NEV market forecasting show more or less consumer-related data which can be further divided into consumer attributes and their demands for daily transport.

As for consumer’s attributes, we already have some studies on consumers’ intention of buying NEV, but we lack studies on their driving behavior patterns which, however, have impacts on driving range, PHEV’s fuel-electricity ratio, usage costs, scrap time and other market forecasting factors, causing deviation in the estimation results on these issues.

As for transport option of consumers, U.S. Department of Transportation (USDOT) has been conducting Nationwide Personal Transportation Survey since 1969, the coverage of which expanded to personal daily transportation and long journey in 2001 (National Household Travel Survey); U.K. Department for Transport has been conducting the National Travel Survey since 1965, and data with continuous time series dates back to 1972; Germany and France also carried out country-level survey on driving range. In China, only a few cities including Beijing and Shanghai have conducted such surveys and their time spans are short, presenting challenges when we try to build national NEV market-forecasting models based on consumers’ transport behaviors.

(3) Policy has strong influence on the market

By considering the drivers behind NEV market, we can see most mainstream models used by western countries are based on Economic Person Assumption which conducts analysis with parameters like energy price and purchase price based on utility maximization theory. In this logic system, market factors are the major drivers behind NEV development.

However in China’s market, policy factors (market admittance, incentives and security control) have significant impacts on NEV market. As suggested in the studies by Ziquan Long et al., if the current incentives remain unchanged, PHEVs adopted from 2013 to 2030 can be as many as 6 times those adopted without incentives, and the peak annual adoption 5.8 times. As suggested in the study by Rengzhi Lü, financial incentives show their best momentum in the second and third month after being launched, which may cause huge market vibration, the impact of which may linger for over 1 year.

Considering great contribution of policies to NEV market, we should incorporate incentives such as subsidies and purchase tax benefits into model factors and preset the policy environment when we build models for future forecasting.

Agent based model is a more real-life model which simulates market development by allowing the interactions among stakeholders, but it poses higher requirements for data and it's hard to build model. Discrete Choice Model studies future market distribution of different vehicle types and shows elaborate results, but it requires data from nationwide consumer survey which has not been established in China. As for Bass Model, it has lower requirement for data, it’s easier to build model and has already widely applied in the study of market diffusion of various innovative products, so it has notable advantages over other models when it comes to building forecasting model for China’s NEV market.

In fact, forecasting is a process of providing reasonable explanation to development trend in future, which is affected by multiple factors including the integrity and time span of historical data, influencer selection, inherent laws among factors, etc. Hence forecasting is a limited reasonable deduction process, which means no forecasting model or method is perfect. One of the key preconditions to accept or use forecasting results for judgment is to admit the limitation of forecasting based on which we can select model parameters and build models for the purpose of the research.

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