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Forecasting Methods for the Electric Vehicle Ownership: A Literature Review

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Abstract

The sustainability issue in the transportation sector brings the electric vehicle (EV) as a new promising solution for reducing carbon emissions. However, the EV adoption faces issues regarding range, recharging time, and high initial investment. To enhance the adoption, supporting infrastructures should be planned. Therefore, forecasting the growth of EV adoption becomes important to help industries and government in strategic decision making. This paper provides a literature review about forecasting methods in EV ownership, which includes studies from 2011 to March 2023. This will contribute to highlight the current methods and stimulating more developments of forecasting methods related to EV ownership.

Keywords: Electric Vehicle; forecasting; EV sales forecasting; EV ownership forecasting; systematic literature review

1. Introduction

The sustainability issue, especially related to the greenhouse effect, is a challenge that has been faced by the entire world, which is caused by fossil fuel combustions. One of the highest contributors to carbon emissions is the transportation sector [1], dominated by road transport [2]. Currently, 95% of conventional vehicles use fossil-based fuel as the main source of energy, which results in increased carbon emissions [3]. To achieve ASEAN 2050 goal, net-zero emission, it is required to implement decarbonization by using lower carbon energy resources and renewable energy to replace fossil fuel usage. Decarbonization is also aligned with the SDGs 7: Affordable and clean energy and SDGs 13: Climate action to reduce carbon emissions by using sustainable energy resources. To reduce carbon emissions from vehicles, one of the emerging technologies is electric vehicles (EV). EV is considered as the most sustainable vehicle for the next decades because it does not emit any carbon dioxide during the vehicle operation [4]. Based on the technology used, EV can be divided into three types: Hybrid Electric Vehicle (HEV), Plug-in Hybrid Electric Vehicle (PHEV), and Battery Electric Vehicle (BEV).

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With the emergence of EV as the sustainable vehicle, identifying the growth of EV adoption through data analytics has become required. There are many factors that influence the EV demand and sales, such as the economic aspect, technology constraints, market potential, government policies, etc. [5]. To uplift EV adoption, other supporting infrastructures and policies should be developed. Forecasting the growth of EV and identifying factors which influence the EV adoption can help the industries and the government in developing strategic planning and decision making. Many studies have been carried out to develop forecasting models with different conditions and situations. However, because EV is considered as a new technology, forecasting EV ownership has its own difficulty due to the lack of previous data. In this paper, a literature review is provided to highlight the current forecasting method and techniques related to EV sales and ownership and to identify the direction for future research.

This paper consists of four sections. Section 2 explains the methodology of literature review. Section 3 provides the extraction results from 47 studies that met the criteria. Section 4 provides a summary and the potential direction for future research.

2. Methodology

A systematic literature review can be defined as a research method and process for identifying and critically examining previous relevant studies, as well as for gathering and analyzing data from the research [6]. A brief methodology in this study is shown in Fig. 1. The literature review is conducted to answer the following research questions:

RQ1 *How extend the development of forecasting method and techniques for EV sales and ownership?*
RQ2 *What factors influenced the growth in EV sales and ownership?*
RQ3 *What advantages and drawbacks from each forecasting method?*
RQ4 *What problems need to be solved as the future direction for EV sales and ownership forecasting research?*

In the literature retrieval process, Scopus is used as the largest database of scientific literature. Publications from journal and conference proceedings are retrieved based on the following TITLE-ABS-KEY: ("electric vehicle" AND "growth" AND "forecasting") and ("electric vehicle" AND "diffusion" AND "forecasting"). From the first search process, 122 publications were found, while from the second process, 54 publications were found. After examining the retrieval results manually from the keywords, it is found that in the EV context, the application of forecasting techniques can be divided into four categories: (1) EV sales and ownership forecasting, (2) electric load forecasting, (3) EV battery forecasting, and (4) energy consumption forecasting. This literature review only focuses on the first category. Then, the filtering process is conducted by matching the paper title and its content with the filtering criteria, which is related only to the EV sales and ownership forecasting topic. After the filtering process, 47 publications met the criteria which were published from 2011 until March 2023. For more than 10 years of time horizons, it should meet the requirement to capture the development of forecasting method. Software ATLAS.ti is used for the review process, especially for helping the author to create quotations and create categorizations of the literature.

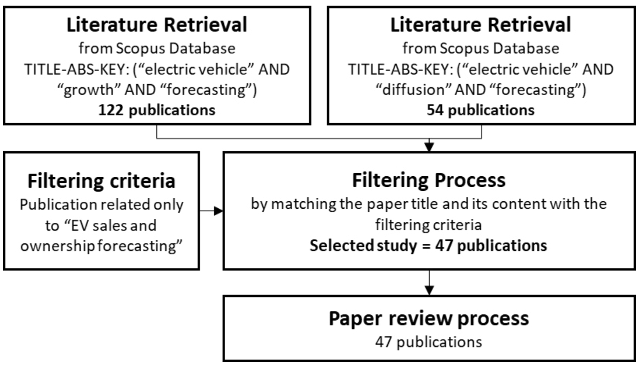

Fig. 1. Methodology of literature study

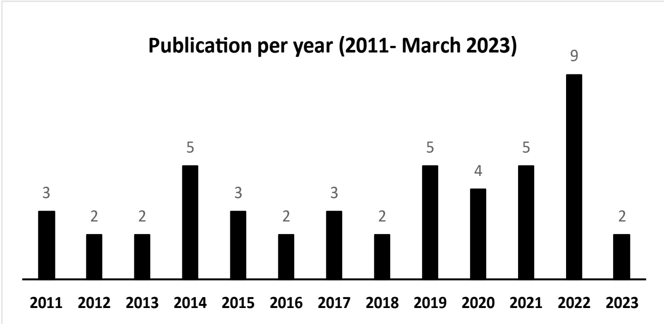

Fig. 2. Publication per year related to EV sales and ownership forecast rom 2011 – March 2023

3. Results

3.1. Retrieval results and forecasting method taxonomy

There are 47 publications that met the criteria: 32 journal articles and 15 conference proceedings, published from 2011 until March 2023. A summary of publication per year is depicted in Fig. 2. In the last three years, publication output related to EV sales and ownership forecasting shows an increase trend. The country that has conducted the most research in this field is China, with 20 publications, followed by United States with five publications, Portugal, and Brazil with three publications each.

EV sales and ownership forecasting methods from literatures are then categorized and summarized in a taxonomy, as shown in Fig. 3. There are four basic forecasting techniques: (1) causal method, (2) statistical time-series, (3) learning model, and (4) mathematical simulation. Most of the previous studies used long-term timeframe for forecasting EV sales and ownership. It is relevant because EV forecasting results is used for planning infrastructures and facilities which are considered as strategic long-term decisions.

3.2. Causal method for forecasting

Causal method identifies the relationships between factors and uses the results to forecast the growth of a product. The most causal method used in the literature is Bass diffusion model. Bass model was developed by Frank M. Bass in 1969 and applied widely for a new product forecasting. In the Bass model, the diffusion of a product is influenced by innovation and imitation rate. An innovator adopts a product by acquiring information from external influences (e.g., social media), while an imitator adopts a product by getting information from internal influences, through word-of-mouth, communications, and observation [7]. In this model, the innovation and imitation rate were set constant along the forecast period [8][9].

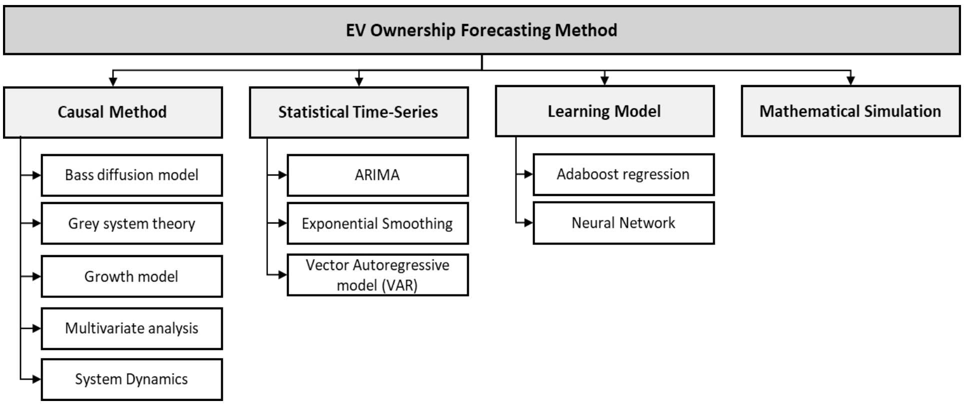

Fig. 3. Taxonomy of EV sales and ownership forecasting method

Because EV is considered as new technology, forecasting processes are sometimes difficult due to the lack of data. Bass model is then extended to adjust with the different situations. In [10], Bass model was applied by using history diffusion data of private cars and the importance of influencing factors were evaluated by using analytic hierarchy process (AHP). The socio-demographic profile was considered in [11] to identify the diffusion variation between each cluster of EV adopters. However, the original Bass model could not capture the socio-demographic influence on the EV diffusion. The Bass model does not always generate the best forecast in every country because of the variety of adoption processes in each country or region [12].

Several studies of EV forecasting used grey system theory, such as GM(1,1) model [13][14][15][16], optimized nonlinear grey Bernoulli model [17][18], and three-parameter grey prediction model (TDGM) [19]. Grey system theory is a useful approach for analyzing uncertain situations and with poor and/or missing information [13]. The combination of Bass diffusion model and grey theory, named grey Bass diffusion model (GBM) was used to forecast new vehicle sales in Malaysia [7]. The grey Bass extended model was developed in [20] which incorporates subsidy policy and price function to model the vehicle demand. Considering grey theory to Bass diffusion model shows a better forecasting result than the original Bass model.

Another diffusion model for EV adoption is logistic growth model [21], which illustrates the life cycle of a product from the introduction phase, growth, maturity, until it is declined or saturated. While, in double species growth model used by [22][23][24], observes the competition of internal combustion engine vehicle (ICE) and EV. The double species growth model basically has four results: (1) species 1 being entirely extinguished, (2) species 2 being entirely extinguished, (3) no global equilibrium point, and (4) reaching global equilibrium point which both being co-existence.

To investigate the influence factors for choosing EV, regression analysis was applied in several studies. The linear regression is conducted in [25], while in [26], multiple linear regression was used based on information about consumer preferences between HEV and ICE. Socio-economic criteria were also considered as predictors in multiple linear regression model for estimating EV ownership spatially [27]. Consumer decision in adopting EV was also modeled using other multivariate analysis, such as probit model [4], logit model [28], conjoint analysis [29], and conjoint logit model [30][31]. The multivariate analysis was also applied with agent-based choice model in [32][33].

The combination of Bass model, grey theory, and multivariate analysis is also found in several studies. The studies in [34] linked multi-criteria analysis and choice modeling for identifying parameters used in diffusion model. In [35], Bass model also combined with disaggregate choice model. The combination of linear regression model and grey theory was also conducted to forecast EV sales in China [36].

Some studies estimated the EV growth with system dynamics. Therefore, system dynamics was applied, which consists of qualitative modeling to identify causal interactions between factors, quantitative or mathematical modeling to simplify the problem, and simulation based on mathematical model [37]. This method was also used to identify car owners' behavior in selecting vehicle technology in Portugal [38].

3.3. Statistical time-series forecasting

There are three studies in EV ownership forecasting which used statistical time-series method. For long-term forecasting, the study in [39] was conducted using ARIMA model. While for short-term forecasting, the Triple exponential smoothing (TES) method was proposed [5]. Although it was applied in the short-term forecast period, some prediction errors could not be avoided due to the large uncertainty and dynamic historical data. Another time-series model was developed for EV forecasting is Vector Autoregressive model (VAR) as a multivariate model. In VAR, socio-economic data was considered in forecasting model. This study showed that the multivariate model is better than the univariate, but VAR requires a large amount of data.

3.4. Learning model

In this category, one of the machine learning techniques, Adaboost regression was applied in [41] to predict EV ownership based on mutual information feature selection related to economic and electricity consumption data. The study showed that in short-term forecast period, Adaboost was more suitable for real data. Meanwhile, the most frequently used method in learning models is neural network. Back Propagation neural network (BPNN) was applied in study [42] to forecast monthly vehicle sales in short-term forecast period. Several influencing factors used in this study, which are seasonal factors, oil price changes, development level of new energy technology, and policy influence. In [43], nonlinear autoregressive neural network (NAR) was compared with grey system theory GM(1,1) to forecast EV ownership including electric buses and passenger cars. The study showed that NAR method has a better performance in forecasting EV numbers. However, forecasting accuracy was highly dependent on the fluctuation of the original data [44]. Meanwhile, instead of comparing forecasting methods, in [45], a combination of forecasting methods was proposed using Bass model, grey theory, and BPNN to forecast EV ownership.

Spatial aspects were also found in two studies using learning models. The study proposed by [46] applied multi-factor prediction model, Bidirectional Long Short-Term Memory (BiLSTM), to forecast EV sales based on electricity and product supply condition, vehicle volume, and cost of ownership. Data was also clustered using K-means method to cluster areas for deciding the EV promotion priority. Spatial distribution of EV was studied by [47] using convolutional neural network (CNN) to support electricity grid planning.

3.5. Mathematical Simulation

Due to data limitations, some previous research developed mathematical simulation which was built based on available data. In [48][51], EV forecasting was estimated based on some scenarios of vehicle diffusion factor. While, in [49][50], the number of vehicles were estimated from the penetration level in each region. However, the forecasting result is highly dependent on the scenarios and the mathematical formulation.

3.6. Data source for forecasting

Most of previous research used year-to-year historical local or regional vehicle sales data as the main data source for EV forecasting. Meanwhile, monthly sales data was also used for a short-term forecast [5] [42]. Because all the studies reviewed in this paper were conducted in different cities and countries, datasets used in each study were also different, depending on the place where studies were conducted. Forecasting with multivariate analysis approach and choice model mostly used local customer data. Internet questionnaire survey was conducted by [4] to householder who has vehicle to get the preference to purchase and use EV. Analogy approach was conducted by [49] using interview to gasoline and diesel vehicle owners to identify customer concerns to a new technology. Stated preference (SP) data also collected from survey in [28] to analyze the influencing factors in choosing a vehicle, while SP data collected twice by [35], before and after respondents experienced an EV.

In several studies, region or area data and socio-economic data were used to analyze spatial differences of EV ownership. Population growth from census data was considered in [28][34] to estimate number of vehicles in a region. Regional data was utilized in [50] to generate EV penetration map based on regional characteristics. Demographic suitability was also considered in [34] as a choice parameter which was used to map spatial distribution of EV at the end of forecast period.

3.7. Factors influencing EV adoption

Because EV is considered as a new technology, in some studies, analyzing only from the historical sales with different forecasting methods still did not make a good forecast. Thus, in developing a forecast model, many factors influencing EV adoption were also considered. In summary, most of forecasting method considered purchase price, fuel price, technology development (e.g., vehicle driving range, fuel efficiency, recharging time), government subsidies or incentives, infrastructure readiness, and socio-demographic characteristics as the influencing factors on EV adoption. Some studies also considered the urban population and economic growth to forecast number of vehicles and the affordability in purchasing EV.

3.8. Forecasting methods advantages and drawbacks

Every EV forecasting method has some advantages and drawbacks, which is explained in Table 1. From this comparison, it can be concluded that the more influencing factors are included in the forecast model, the better the results. Applying machine learning methods could predict the future EV adoption better by recognizing the historical pattern and understanding influences among datasets. However, considering lots of influencing factors and using lots of data requires more complex analysis and computation.

Table 1. Advantages and drawbacks of EV forecasting methods

Ref.	Main method	Advantages	Drawbacks
[8][9] [10][11] [12]	Bass diffusion model	Widely used as a forecast for new product demand.	Does not consider other specific factors on the diffusion of technology; only suitable in a stable market condition.
[13][14] [15][16] [17][18]	Grey system theory	Can deal with small sample of data and uncertainty; does not require the use of numerous associated factors.	Lots of mathematical calculation, poor fitness, and low accuracy when the data is changed; does not suitable for long-term prediction.
[7][19] [20]	Grey Bass diffusion model	Can deal with small sample of data and uncertainty; can consider other influencing factors of diffusion.	Lots of mathematical calculation; does not consider the market change along the forecast period.
[21]	Logistic growth model	The curve is more realistic for modeling the life cycle of a product.	Ambiguity in modeling the market's carrying capacity.
[22][23] [24]	Double species model	May catch the interactive influence feature of different type of product penetration.	Need to generate probable scenarios; need to include variations of inference effects according to resource dynamics.
[25]	Linear regression	Can identify the factor's influence on the adoption of product; easy to implement and to interpret.	Limited to the assumption of linearity between dependent and independent variables; prone to mistakes and outliers.
[26][27]	Multiple linear regression	Can consider other factors that influence the diffusion of technology.	Does not explicitly consider the vehicle market competition; limited to the assumption of linearity between dependent and independent variables.
[4][28]	Logit, Tobit, Probit model	Show the demand shifts in the presence of a new alternative product; can identify the feature importance of a new product adoption.	Need to consider the market and preference change in the future.
[29][30] [31]	Conjoint analysis	Show the preference in adopting a new product; combine information from the choice modeling and historical market penetration.	Need to consider the market and preference change in the future.
[32][33]	Agent-based choice model	Show the preference in adopting a new product based on social media influence.	Need to consider the market and preference change in the future.
[34][35]	Bass diffusion & choice model	Replacing the probability of adopting a new product with choice model.	Need sufficient data to estimate the coefficients of the diffusion model.
[36]	Grey linear regression	Can consider other influencing factors of diffusion; eliminate the influences of uncertain factor.	Needs to collect data and influencing factors as much as possible for a better accuracy.
[37][38]	System Dynamics	Can model the complex system; show the connection and interaction of the consumer behavior factors.	Only capable to run one situation at a time; need a strong theoretical background to model the connection and interaction between factors.
[5][39]	Exponential smoothing: ARIMA, TES	Can account for various patterns, trends, and seasonal or non-seasonal fluctuations.	Does not suitable for multivariate time series data; cannot capture the interactions and dependencies between different variables.
[40]	Vector autoregressive model (VAR)	The model explains better than univariate method; can capture the dynamic interactions among multiple variables.	Requires large amount of data; does not account the nonlinearities of data.
[41]	Adaboost regression	Less prone to overfitting	Requires high computational process; sensitive to noisy and error data.
[42][45]	BPNN	Does not require any parameters tuning; does not require prior knowledge about the network.	Require high computational process; sensitive to noisy and error data; performance is highly dependent on input data.

Table 1. Advantages and drawbacks of EV forecasting methods (continued)

References	Main method	Advantages	Drawbacks
[43][44]	NAR Neural Network	Accept dynamic inputs represented by time series sets to predict future values from the past.	The accuracy is highly dependent on the fluctuation of data; need to re-train when new parameters are included into the model.
[46]	BiLSTM	Can learn long-term dependencies and capture complex patterns in sequential data.	Require high computational process; require more time to train and run the model.
[47]	CNN	Can deal with spatial data using complex images.	Requires large datasets to achieve high accuracy; requires high computational process
[48][49][50] [51]	Mathematical Simulation	The model is built based on the given scenarios and available data.	The result is dependent on the included parameters and built scenarios.

4. Potential Future Research

From the literature review process related to EV sales and ownership forecasting model, there are three potential directions for future research:

- Because EV is considered as a new technology, many factors influence people to choose and use EV. Learning model application for predicting individual choice is a promising approach to get a better prediction based on the variety and large volume of data.
- According to diffusion theory, social media is one of the effective ways to influence people to adopt a new technology. There are potential data mining approaches, such as opinion mining, web mining, and text mining which can be applied to capture insights from social media and to measure the diffusion effect from social media about a new emerging technology.
- Based on studies conducted by [46] and [47], the factors influenced differently in each region because of the uneven regional characteristics. Therefore, spatial analysis can be applied to get a better forecast for each region. It is also useful for strategic planning to decide the priority.

5. Conclusion

Nowadays, electric vehicles are considered as new promising sustainable vehicles for the future. Therefore, facilities and infrastructures are required to support EV adoptions. However, due to the high investment cost of facilities and infrastructures, planning and decision should be made strategically based on EV adoption growth. To support the strategic planning, EV ownership forecasting is needed. This paper explains a literature review about EV sales and ownership forecasting model to highlight the current proposed model and to identify research future directions.

In this literature review, 47 publications were studied related to EV sales and ownership forecasting, from 2011 to March 2023. From the review process, most of the research proposed long-term forecasting to support long-term planning of infrastructures. There are four approaches for forecasting EV sales and ownership: causal method, statistical time-series, learning model, and mathematical simulation. The causal methods such as diffusion model and multivariate analysis are the most frequently used for EV forecasting. However, with the emerging big data and data mining techniques, recent studies used machine learning and neural networks to predict EV adoptions. Some advantages and drawbacks of each forecasting method are explained for comparison. Lastly, for future research, utilizing more data analytics techniques is needed to get a better forecast. More exploration in spatial aspects is also needed to capture the differences of factors influencing EV adoption in each region.

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