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Forecasting the Number of End-of-Life Vehicles: State of the Art Report

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Abstract

Academics and practitioners have shown a growing interest in automobile reverse supply chain (RSC) management as a result of the rise of circular economy and the development of Industry 4.0. Accurate quantity prediction enhances the efficiency of all decision levels in automobile RSC, not only the recovery of end-of-life vehicles (ELVs). Therefore, a comprehensive state-of-the-art review, evaluating ELVs quantity forecasting methodologies and summarizing the main variables influencing forecasting outcomes, is conducted to throw shed light on future research directions.

Keywords: sustainability, design review, circular economy, change prediction

1. Introduction

The circular economy business model promotes the closure of material loops in the supply chain through reusing products (Kosacka-Olejnik, 2019). Industrial businesses have incorporated the "3R" principle of circular economy (reduce, reuse and recycle) into their product recovery processing system (Tian and Chen, 2014). Recycling is one of the most significant methods for reducing landfilling and other general environmental pollutants, and enhancing industrial efficiency (Alwaeli, 2016). Recycling, in the context of automotive reverse supply chain (RSC) management, refers to the conversion of end-of-life vehicles (ELVs) into resources that can be used in the vehicle remanufacturing process.

The final productive use of the components and materials embedded in ELVs is characterized as ELVs recovery (Despeisse et al., 2015). ELVs are collected through collection points in various consumption regions, then some ELVs are transported to an inspection center where the technicians disassemble and test them with professional equipment (see Figure 1). The ELVs processing flow is nearly identical in many countries, involving depollution, dismantling, shredder, air classifier, landfilling, etc. (Wong et al., 2018). There are numerous recyclable resources (i.e., steel, copper, rubber, etc.) and harmful compounds (i.e., lubricants, acid solutions, coolants, etc.) contained in scrapped vehicles (Hu and Wen, 2015). High-value auto parts can be remanufactured after detection and classification, while other parts are delivered to the waste disposal center. In conclusion, the whole automotive RSC process shows high uncertainty in terms of time, quantity, and quality.

In certain developing nations, the ELVs quantity is anticipated in a conventional way with limited accuracy, using an empire multiply factor of 5% - 8% of the total number of vehicles (Xin et al., 2018). In this case, most ELVs tend to flow into illicit markets or recycle dealers through various informal channels rather than being returned it to original equipment manufacturers, leading to resource waste, safety hazards, and unsustainable development (Li et al., 2019). For example, in 2020, a total of 3.24 million ELVs have been discarded in China, yet only 74% is recycled. By improving the accuracy of the prediction model, the national prediction level of ELVs quantity can be enhanced

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further, reducing pollution and maximizing the value of resources. More particular, effective ELVs prediction guides the formation of policy and legislation for the government (Azmi and Tokai, 2017). For automotive industries, accurate predictions help automotive firms in designing development strategies, profit projections, and market evaluations (Yu et al., 2019). More specifically, effective ELVs prediction is essential for all decision levels of the RSC for industrial engineers, including strategic reverse logistics network design, tactical disposal management and capacity planning decisions, and operational production planning decisions (Toktay et al., 2004), assisting organizations in connecting their raw materials, remanufacturing operations, manufacturing capabilities, systems and clients. Besides, in the face of multiple quantity forecasting methods, there is a lack of comprehensive review of the concept, influence factors, and application of ELVs quantity forecasting methods. Hence, it is vital to review the forecasting methods of ELVs quantity so as to assist researchers in selecting the appropriate forecasting methods.

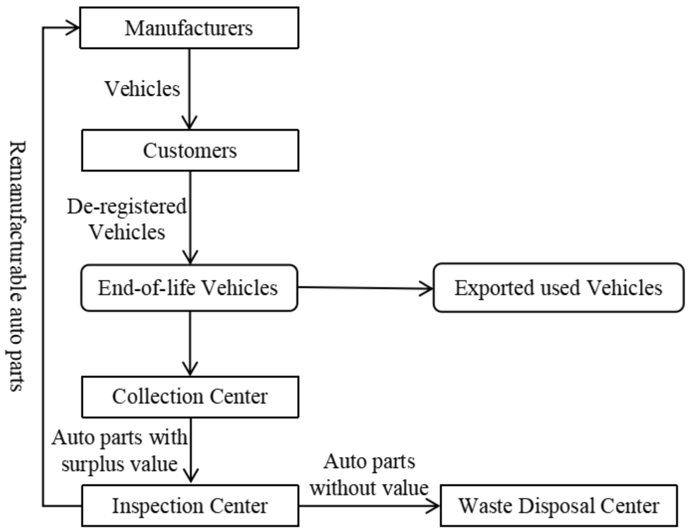

Figure 1. Automotive reverse supply chain (RSC) process (Kanari et al., 2003)

The focus in this paper is to review the research methods and their application in ELVs number forecasting, summarize influence factors that affect forecasting results, and prospect the future research direction. The paper is organized as follows: The research background is introduced in Section 1. The research statement is presented in Section 2. A detailed literature review of the forecasting methods and the influence factors affecting the outcomes of the projection is shown in Section 3 and Section 4 respectively. Future research directions are discussed in Section 5. The paper is then concluded in the last section.

2. Research methodology

As discussed in the Section 1, the aim of this paper is to present a comprehensive review related to forecasting the number of ELVs based on the literature. More specifically, the following research questions are addressed in this paper:

1. What forecasting methods have been used to predict the number of ELVs?
2. What influence factors are considered when making predictions?
3. What are the future directions for forecasting the number of ELVs?

A state-of-the-art review is conducted to answer these three research questions. Five scholar databases have been searched, including Science Direct, SCOPUS, Web of Science, Research Gate and Google Scholar. The following keywords are searched: "the number OR quantity OR amount of ELVs", "prediction OR forecasting OR projection". Moreover, the references listed are further explored to identify other sources of information. The contributions of this review are as follows:

- The publications published between 2001 and 2021, including journals and conference papers, have been considered in this comprehensive review.

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- Forecasting methods for ELVs quantity in this paper have been divided into traditional and intelligent methods, and the characteristics of each forecasting method have been analyzed.
- Influence factors affecting the forecasting results have been summarized.

Guided by the three research questions, the following paper is organized into three discussion topics and a conclusion as an extended discussion:

- Discussion One: The methods applied to forecasting ELVs quantity, as well as their benefits and drawbacks (see Section 3).
- Discussion Two: The influence factors affecting the outcomes of the projection (see Section 4).
- Discussion Three: A discussion of future opportunities and research directions (see Section 5).

3. Discussion one: forecasting methods of the number of ELVs

The forecasting methods are divided into Traditional and Intelligent models (see Table 1). In the following sections, we will discuss each method briefly and thoroughly analyze the relevant literature.

Table 1. A complete list related to forecasting method of recognized articles

References	Type of Vehicles	Forecasting Methods						Forecasting Period
		GM	RM	PBM	TS	SM	IM	
(D'Adamo et al., 2020)	ELVs		√					Until 2023
(Zhou and Ma, 2020)	ELVs	√						2019
(Wang et al., 2020b)	ELHVs		√					Until 2030
(Li et al., 2020)	ELVs					√		2020-2030
(Xu et al., 2019)	ELVs			√				2015-2040
(Yu et al., 2019)	ELVs			√				2018-2025
(Wang et al., 2019)	ELHVs		√					Until 2030
(Lin et al., 2018)	ELVs			√				1960-2050
(Xin et al., 2018)	ELVs						√	2016-2020
(Hao et al., 2018)	ELVs						√	2005-2016
(Ene and Öztürk, 2017)	ELVs	√						2016-2020
(Ochotnicky et al., 2017)	ELVs				√			Until 2020
(Demirel et al., 2016)	ELVs			√				2012-2022
(Sokić et al., 2016)	ELVs					√		2015-2025
(Li and Wang, 2015)	ELVs	√						2015-2024
(Yano et al., 2015)	ELHEVs			√				2010-2030
(Tian et al., 2013)	ELVs						√	1995-2012
(Hu and Kurasaka, 2013)	ELVs					√		2015,2017,2020
(Yano et al., 2013)	ELVs			√				2011-2020
(Phornprapha et al., 2010)	ELMs		√					2011-2040
(Andersen et al., 2007)	ELVs			√				2005-2030
(Kilde and Larsen, 2001)	ELVs			√				Until 2015

*GM: Grey Model, RM: Regression Model, PBM: Population Balance Model, TS: Time Series Model, SM: Statistical Model, IM: Intelligent Method, ELHVs: End-of-life Hybrid Vehicles, ELHEVs: End-of-life Hybrid Electric Vehicles, ELMs: End-of-life Motorcycles.

3.1. Traditional forecasting methods

3.1.1. Grey model (GM)

As one of the most important systems for forecasting, the grey system is appropriate for "small sample, poor information", which means the future development trend of a system can be predicted through mining and analyzing a tiny portion of known data (Julong, 1989).

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Li and Wang (2015) evaluated the current state of auto production, car ownership and ELVs in China according to the changing rule of real data from 2005 to 2014, and applied the GM (1,1) model and MATLAB software to estimate the number in a decade. Given the features of return flow and the benefits of grey system theory, Ene and Öztürk (2017) created a forecasting system suitable for data sets with high uncertainty and small size to estimate ELVs returns. The proposed forecasting system is made up of four sub-models, including the basic GM (1,1) model, the parameter optimized grey model (OGM), the grey forecasting model with parameter optimization and Fourier series modification (FOGM), and the improved form of the OGM and FOGM models with Markov chain correction (MFOGM). The proposed forecasting system is applied to the case of Turkey, taking the most recent data of twelve regions in Turkey from 2008 to 2013 into account. Moreover, Zhou and Ma (2020) developed a modified forecasting GM (1,1) model to predict ELVs recycling by integrating the residual error with the basic GM (1,1) model. The proposed forecasting GM (1,1) model, traditional GM (1,1) model and non-linear regression forecasting model are compared in the experimental analysis taking ELVs recycling amounts from 2015 to 2018. The result reveals that both the modified GM (1,1) model and the nonlinear regression model excel on forecasting, with the modified GM (1,1) model outperforming the nonlinear regression model with a lower average deviation.

3.1.2. Regression model (RM)

Regression modelling is to establish a function relationship between dependent variable and independent variable based on a large number of historical data, which is applicable to non-stationary time series with an obvious trend of change.

Through a linear regression model, a good relationship between ELVs waste streams and the economy is demonstrated, namely Gross Domestic Product (GDP), Purchasing Power Standard (PPS) and social factors (e.g. population), and this conclusion is also corroborated by the dynamic model (D'Adamo et al., 2020). This model can be used to forecast future trends in Europe until 2030. For validation, a comparison study of European ELVs flows classifies Member States' performances into three groups (i.e., high performer, in-between and low performer) based on three indexes, namely the percentage of recycled ELVs, the ratio of recycled ELVs to GDP and the ratio of recycled ELVs to population.

Moreover, Wang et al. (2020b) attempted to analyse the recyclable end-of-life hybrid vehicles (ELHVs) numbers using the actual vehicle deregistration rate in Japan while taking secondhand HVs sales into consideration. The scenario analysis on the used HVs exportation is further examined to make a more accurate estimate on the quantity of ELHVs in Japan. Based on the fact that Mongolia imported a huge number of used HVs from Japan, Wang et al. (2019) provided a RM for predicting the ELHVs numbers in Mongolia, taking into account the remaining rate of HVs and the number of exported secondhand HVs. Further, the cohort method is developed to predict the number of end-of-life motorcycles (ELMs) in each subsequent year (Phornprapha et al., 2010).

3.1.3. Population balance model (PBM)

The population balance model (PBM) is a dynamic forecasting model defined by the mass balance between input, stock, and output of materials or products with a lifespan (Yano et al., 2013).

Lin et al. (2018) applied PBM to calculate the ELVs quantity based on the shipment number, possession number, and lifespan distribution. The findings indicate that the number of ELVs generated in Kinmen would rise significantly, implying that ELVs treatment capacity should be increased in the future. Moreover, Yano et al. (2013) used PBM and a Weibull distribution for the lifespan distribution to estimate the number of ELVs in Japan during 2011-2020. Similarly, Demirel et al. (2016) built PBM using historical data on population, GDP, car ownership, and vehicle life distribution. To gain the number of ELVs generated in Japan during 2015-2040, three important variables are required, including the number of registered vehicles, the remaining ratio of vehicles and the exported used vehicles (Xu et al., 2019). Only the number of domestic end-of-life hybrid electric vehicles (ELHEVs) are predicted, with no consideration given to exported ELHEVs (Yano et al., 2015).

Yu et al. (2019) considered government measures (i.e., subsidy policies and aggressive policies) that were significant for both the recovery rate of ELVs (R-value) and the distribution function of

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passenger vehicles, and estimated the number of ELVs for passenger vehicles and commercial vehicles in China. To develop the model, three factors (i.e., vehicle sales, vehicle ownership, and the life distribution model) are investigated. In order to forecast the ELVs quantity in 16 European Union accession nations till 2015, Kilde and Larsen (2001) presented a model, considering vehicle lifespan defined by a modified Weibull distribution and vehicle density described by a three-parameter Gompertz function. For validation, a basic scenario and sensitivity analyses on the saturation level for vehicle density and the mean lifetime of vehicles are carried out. Likewise, Andersen et al. (2007) used a Weibull distribution for vehicle lifespan and a GDP-dependent Gompertz function for vehicle density to estimate the ELVs quantity in 25 EU Member States until 2030.

3.1.4. Time series (TS) model

Time-series predicting is the process of forecasting the future direction and degree of its change of a variable based on a large number of experimental samples (Hamilton, 2020).
Based on the number of registered vehicles and deregistered vehicles, and the general economic status of families and businesses in the Slovak Republic, a forecasting framework that combines TS model with expert judgement is constructed. Ex-post validation of the ex-ante projections is also provided using new, forward-looking data, showing the forecasting system's accuracy (Ochotnicky et al., 2017).

3.1.5. Statistical model (SM)

The statistical model depicts the probabilistic connection between different random variables, which requires huge sample data sets and prior knowledge when applied to product return flow management (Ene and Öztürk, 2017).
The statistical distribution of the number of ELVs is defined by a normal distribution given by the two-parameter Weibull distribution function in (Sokić et al., 2016), forecasting ELVs generation over a 10-year span in Serbia. Additionally, based on the estimates of new vehicle demand, survival rate, and vehicle ownership, Weibull distribution functions are used to forecast the generation of ELVs in China from 2020 to 2030 (Li et al., 2020). Hu et al. (2013) also developed a projection model for ELVs distribution per population in 31 province-level areas of China in 2015, 2017, and 2020 under three scenarios and compared the projected findings with the current distribution and capacity of certified ELVs processors in China, discovering that the main notable feature is the unbalanced ELVs generation among provincial regions.

3.2. Intelligent forecasting methods (IM)

Intelligent forecasting is a method for predicting the number of ELVs using artificial intelligent (AI) technology. AI could be described as intelligent programs, algorithms, systems or machines (Shankar, 2018), which have strong skills to address nonlinear issues (Roozbeh Nia et al., 2021).
Xin et al. (2018) presented a comparative study on two novel intelligent forecasting approaches for Chinese ELVs: a general regression neural network (GRNN) and an optimized GRNN based on an artificial bee colony (ABC-GRNN). According to the simulation findings, both approaches can predict the number of Chinese ELVs accurately, and the ABC-GRNN outperforms the GRNN in terms of fitting accuracy, generalization ability and forecasting errors. Additionally, considering 10 factors impacting the recycling of ELVs and the interactions among these factors, Hao et al. (2018) provided a hybrid prediction model consisting of a grey model, exponential smoothing, and a back propagation neural network (BPNN) optimized by the particle swarm optimization (PSO) algorithm. Then an empirical study is conducted and indicates that the hybrid model GM (1,1)-TES-GM (1,N)-PSOBP obtains the best performance. Moreover, multiple linear regressions (MLR), neural networks (NN) and optimized NN based on genetic algorithm (GA-NN) methods have been used to develop prediction models of ELVs volume based on collected major factors and historical data. A numerical example is provided to demonstrate how the GA-NN model outperformed the MLR and NN (Tian et al., 2013).
To summarize, the benefits and drawbacks of frequently utilized approaches for ELVs quantity prediction are described, as shown in (Table 2).

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Table 2. Summary of most used forecasting methods of ELVs quantity

Method	Advantages	Disadvantages
Grey Model	Require less data; no requirement for data with a regular distribution; high prediction accuracy; strong ability of systematic error prediction; appropriate for forecasting in the short and medium term. (Ene and Öztürk, 2017)	Incapable of recognizing the oscillation characteristics in the original sequence; poor ability of predicting random errors; inability to dynamically reflect system changes. (Zhou and Ma, 2020)
Regression Model	Appropriate for non-stationary time series with a clear changing trend; applicable for multi-factor models; capable of demonstrating correlation between factors. (Wang et al., 2019)	Low prediction accuracy; sensitive to outliers; poor generalization ability; inappropriate for a system with strong randomness. (D'Adamo et al., 2020)
Population Balance Model	Capable of maintaining mass balance between input, outflow and stock; dynamically applicable for estimating recovery products' past, present, and future. (Lin et al., 2018)	Ineffective for estimating products in quick growth and decline stages; unsuitable for products with an unstable lifespan distribution. (Yano et al., 2015)
Time Series Model	Have the capacity to correct the local data trend; define the time point properly; offer a confidence interval for the prediction findings; suitable for stationary time series without missing samples. (Hamilton, 2020)	Require a large amount of stable historical data; inappropriate for dealing with nonlinear issues; model parameters are difficult to identify. (Ochotnicky et al., 2017)
Statistical Model	High prediction prediction; require fewer computational resources; make rapid predictions given data that meets the models' requirements. (Li et al., 2020)	Poor prediction performance due to data that does not satisfy the models' assumptions. (Sokić et al., 2016)
Neural Network	Highly robust; no need to specify a prior probability; have excellent fault tolerance and nonlinear modelling capabilities; provide fast search for optimal solutions through self-learning functions. (Hao et al., 2018)	Inability to explain reasoning process and reasoning basis; have a risk of over-fitting; requires a significant amount of training data, training procedure is time-consuming; converting reasoning to numerical calculations leads to information loss. (Xin et al., 2018)

4. Discussion two: influence factors

Some scholars use ELVs quantity to make the fitting prediction directly. Since ELVs management has only emerged in recent years, there is little accurate and sufficient data available. Some scholars make prediction by taking influence factors that affect ELVs quantity as the input variables in prediction (see Table 3). Most of the influencing factors can be searched in National Bureau of Statistics. However, different terms are often used in various articles but indicating the same influencing factor. These factors using various terms are discussed as follows, with necessary explanations.

Vehicle Ownership - Vehicle ownership could also be described as "The Stock of Vehicles" (Demirel et al., 2016). The number of automobiles owned in a given year is referred to as vehicle ownership (Yu et al., 2019). The number of vehicle ownership is obtained by multiplying the population by vehicle ownership per capita (Lin et al., 2018).

Number of discarded vehicles - Discarded vehicles can be seen as "Deregistered Vehicles", including automobiles returned by their end users as well as fully damaged vehicles obtained from insurance companies (Ochotnicky et al., 2017).

Vehicle Scrap Rate - Vehicle Scrap Rate is sometimes known as "Discard Rate" (Lin et al., 2018), and may be described as "ELV population during a given year/Vehicle population during an indicated year" (Hu and Kurasaka, 2013).

Sales Volume - Sales volume is also known as "Shipment Number", which could be defined as the following equation (Equation 1) (Lin et al., 2018):

$$SVt= Nt - Nt\text{-}1 + Gt \tag{1}$$

In this equation, N_t means the number of vehicle ownership, and G_t implies the number of ELVs.

Survival rate - Vehicle data recorded by vehicle age should be utilized to determine the optimum vehicle survival rate (Phornprapha et al., 2010).

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Lifespan distribution - The lifespan of a vehicle might be seen as the remaining ratio of vehicles (Wang et al., 2020b), which is usually defined as the period between the fiscal year when it is first registered and the fiscal year when it is finally canceled (Yano et al., 2015). There are various methods for calculating the vehicle lifespan distribution, such as Weibull distribution (Lin et al., 2018).

Table 3. A complete list related to influence factors of recognized articles

References	Number of auto production	Vehicle ownership	Number of discarded vehicles	Number of registered vehicles	Vehicle scrap rate	Sale volume	Remaining rate of vehicles	Survival rate	Lifespan distribution	Number of exported used vehicles	Highway freight turnover	Passenger turnover	Gross domestic product	Population	Highway mileage	Income of per urban resident	Recycled material price	Recycling price	Number of industrial employees	Fixed asset	Number of collection node
(Wang et al., 2020b)		√				√				√											
(Li et al., 2020)		√						√	√												
(Zhou and Ma, 2020)			√																		
(D'Adamo et al., 2020)													√	√							
(Xu et al., 2019)				√					√	√											
(Yu et al., 2019)		√				√			√												
(Wang et al., 2019)									√	√											
(Lin et al., 2018)		√				√			√												
(Xin et al., 2018)	√	√				√					√	√	√			√					
(Hao et al., 2018)		√											√	√	√	√	√	√	√	√	√
(Ene and Öztürk, 2017)			√																		
(Ochotnicky et al., 2017)			√	√																	
(Demirel et al., 2016)		√							√				√	√							
(Sokić et al., 2016)	√		√																		
(Yano et al., 2015)				√			√		√												
(Li and Wang, 2015)	√	√																			
(Hu and Kurasaka, 2013)		√			√								√	√							
(Tian et al., 2013)	√	√				√					√	√	√			√					
(Yano et al., 2013)		√							√												
(Phornprapha et al., 2010)				√				√					√								
(Andersen et al., 2007)		√							√					√							
(Kilde and Larsen, 2001)		√							√					√							

5. Discussion three: future opportunities and research directions

To summarize, we recommend five future ELVs quantity forecasting research directions for enhancing prediction accuracy and boosting the efficiency of automotive RSC, which are as follows:

In this paper, the forecasting methods of ELVs quantity are classified into traditional and intelligent methods (see Table 1). Traditional forecasting methods are used in most studies, and perform well when dealing with general linear issues. Instead, nonlinear sequences in ELVs recovery quantity cause prediction

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accuracy to be unstable because of the significant degree of uncertainty in automobile RSC. In this field, only artificial neural networks are currently used, like GRNN and BPNN. Hence, AI is expected to be increasingly widely applied in predicting ELVs quantity, potentially improving the accuracy and reliability of prediction results. It can be concluded that some AI technologies, such as Machine Learning (ML), Fuzzy Logic, and others, are rarely utilized to tackle the nonlinear characteristics and uncertainty in ELVs quantity. Thus, we propose Research Direction 1.

- Research Direction 1: More ML-based models, such as Support Vector Machine (SVM), Decision Tree (DT) and K-Nearest Neighbours (KNN), should be explored in building ELVs quantity forecasting models.

Most scholars tend to use single prediction models with limited prediction accuracy (see Table 2). Moreover, it is challenging to describe nonlinear and dynamic growth tendencies in ELVs recovery using a single model. The development of a hybrid prediction model is required. A hybrid model combines the predictions of various forecasting methods to create new predictions (Wang et al., 2020a), which is an efficient and stable way to overcome the constraints of each component model and increase forecasting performance (Wang et al., 2017). Hence, we put forward Research Direction 2.

- Research Direction 2: A hybrid forecasting model integrating linear and nonlinear models should be utilized to enhance the accuracy in forecasting ELVs quantity. Additionally, a combination of traditional and intelligent forecasting methods should also be investigated.

Limited samples could be obtained for ELVs recycling forecasting as a result of the immaturity of ELVs industry and the absence of standard regulations in some countries and areas (Zhou and Ma, 2020). In general, a large amount of data is required to construct a prediction model, but there is insufficient data to fit and test a forecasting model. For this reason, Research Direction 3 is proposed.

- Research Direction 3: Prediction methods for small samples should be further expanded when developing the ELVs quantity forecasting model.

Regarding socioeconomic influence factors, some papers mainly focus on some basic variables, such as vehicle ownership and lifespan distribution, while others, such as exported used vehicles, receive less attention. Even though there are numerous known influence factors (see Table 3), others, such as the number of vehicle drivers, have yet to be identified. In addition, few papers have investigated the interrelationships between these influencing factors. Therefore, we bring forward Research Direction 4.

- Research Direction 4: Influence factors related to other end-of-life high-value products need to be referenced and the dynamic relationship between these influence factors should be investigated, in order to improve the model's generalization capacity and prediction accuracy.

Given the uncertainty of ELVs recycling, more social factors regarding returning ELVs should be addressed. For instance, it is necessary to explore the effects of various policies (i.e. education of environmental protection knowledge, improved laws and regulations, economic subsidies and preferential policies) on the quantity of ELVs generated. As a result, Research Direction 5 is advanced.

- Research Direction 5: Simulating consumer decision-making on returned ELVs under various policies could improve prediction accuracy.

6. Conclusion

This paper presents a comprehensive review of ELVs quantity forecasting in the literature published from 2001 to 2021. Based on this literature review, forecasting methods have been categorized as Traditional and Intelligent models (see Table 1). Following that, the advantages and disadvantages of the commonly used methods are explained (see Table 2). Moreover, a comprehensive list of 21 major factors impacting forecasting outcomes has been summarized (see Table 3).

This paper has addressed three research questions, and proposed five future research directions in prediction models and influence factors of ELVs quantity, with the goal of reviewing the research methods and their application in ELVs number forecasting and summarizing influence factors that affect forecasting

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results. This paper is thoughtful to be useful as a reference and to assist scholars in creating new research directions connected to ELVs quantity forecasting.

However, there are a few limitations that could be addressed in future research. First, the number of articles retrieved from the stated five scholar databases is limited, and more sources could be explored in further studies. Second, in terms of influence factors, there is a need in future research to conduct quantitative analysis to identify the most significant one.

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