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Mathematical Model and Prediction Analysis of Automobile Power Battery Decommissioning Based on Weibull Distribution

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Abstract: *With the significant increase of lithium battery consumption in China, resource safety is widely concerned by the industry. However, the industry lacks relevant models for the specific temporal and spatial prediction analysis of retired batteries, and how to determine the future amount of retired new energy vehicles has become a hotspot in the industry. In this paper, based on the data of the national new energy vehicle sales terminals, the Weibull distribution is used to construct the retirement volume model, and the model parameters are calculated by vehicle type to realize the spatial and temporal prediction analysis of the retirement of the retired power battery. The model has good interpretation, and has strong correlation in 51% of the model data and correlation in 90% of the model data, which can provide a theoretical basis for the industry layout and research.*

Keywords: *Weibull Distribuion, New Energy Vehicle, Retired Batteries*

1. Introduction

As a national strategic emerging industry, new energy vehicles have developed vigorously in recent years. Especially after 2015, driven by related national subsidy policies and the rapid development of domestic supporting technologies such as batteries and motors, the cumulative output of new energy vehicles in China has exceeded 4.5 million, and the cumulative supporting battery capacity has exceeded 220GWh. With the significant increase of lithium battery output, the safety of metal resources used in lithium batteries has been widely concerned. According to the prediction of Statista, an international research institute, the global annual consumption of lithium carbonate will reach 820,000 tons in 2025, about 2.7 times that of 2019, which poses a resource risk for the sustainable development of lithium battery industry. According to the prediction of relevant industry institutions, the decommissioning volume of power batteries in China will exceed 200000 tons in 2020 [1]. Retired batteries can be used for echelon utilization, or valuable metal elements such as lithium, cobalt, nickel, copper, aluminum and other materials such as graphite can be extracted through comprehensive utilization of resources.

However, due to the immature supporting industry and other factors, there is great pressure on the recycling, logistics and comprehensive utilization of retired batteries. Among them, the layout problem is difficult for many enterprises. The sales distribution of new energy vehicles in China is greatly affected by the promotion policies. The promotion time, quantity and type of vehicles in various cities are quite different, and there are great differences in the pressure of decommissioning and recycling of power batteries in various regions. If the facilities cannot be built in a targeted way, it may lead to the double contradiction of overcapacity and shortage in some areas. Therefore, efficiently predicting the decommissioning of new energy vehicles in various regions of the country can provide a scientific basis for the management department to organize the management of battery recycling, and is also conducive to the industrial planning and layout of relevant enterprises in the industry.

As a new hot spot in the industry, the prediction of power battery decommissioning has attracted the attention of research institutions [2-5]. In order to establish the product life model, academic circles have conducted extensive theoretical research. At present, the mainstream forecasting method is to forecast the vehicle production data in combination with the warranty period. For example, Liu Guangfu [6] estimated the scrap amount and potential resource amount of power battery based on a small amount of industry public data, Peng Jielin [7] predicted the scrap amount of power battery using Stanford model with a small amount of industry public data, and Zhang Shuying [8] and others used Monte Carlo

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simulation to calculate. The above methods build empirical models by empirically assuming the service life of new energy vehicles, and predict the scrap volume based on macro data. The prediction reliability of the model is greatly affected by the preset parameters. In addition, due to the data samples used, the prediction accuracy is low, so the above prediction methods cannot be modified, and can only be used as a reference for theoretical analysis.

Based on the new energy vehicle terminal data, aiming at the product reliability and life test, this paper uses Weibull distribution to carry out the theoretical basis of the retirement prediction model. This theory was explained in detail by the Swedish mathematician Waloddi Weibull in 1951, and it can cover the life distribution of products with various characteristics. In this paper, the decommissioning quantity of new energy vehicles is modeled and analyzed, and the vehicle scrapping quantity parameters are calculated and predicted by vehicle types.

2. Data collection and analysis

2.1 Data feature analysis

The data used in this paper are the announcement of new energy vehicles by the Ministry of Industry and Information Technology, vehicle certificate and traffic insurance data, with a total of about 4.13 million vehicles. Among them, 3.41 million vehicles were produced in 2012-2019, which can be used for model building. These vehicles are distributed in 31 provinces, autonomous regions and municipalities. Based on the fact that the vehicle can't enjoy the preferential treatment if the traffic insurance is overdue for 3 months, we assume that the vehicle will be stopped if it fails to pay the traffic insurance for 90 days. According to the classification of the decommissioning of new energy vehicles, a total of about 3.029 million vehicles are in use, and about 380,000 vehicles are out of service. The comprehensive decommissioning rate is about 11.1%. The data set includes vehicle model, manufacturer, usage city, stop-use month, number of vehicles, and some vehicle parameter information, which is used to support related analysis.

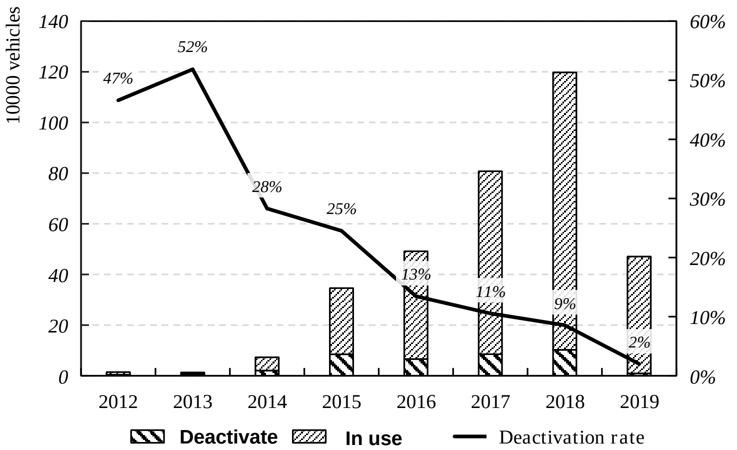

Figure 1: Distribution of the ratio of production of new energy vehicles to be discontinued in each year

Make an overall analysis of the deactivated data. As can be seen from Figure 1, there is a significant negative correlation between the production year and the probability of vehicle deactivation, and the probability of vehicle deactivation also increases with the increase of service time. In 12 and 13 years, the vehicle stopping rate was 47% and 52% respectively, which was much higher than the average of 11%, while in 17-19 years, the vehicle stopping rate was lower than the average of 11%, 9% and 2% respectively.

The outage rate of new energy vehicles is closely related to the loss of batteries. According to related reports, because there are many types of batteries used in new energy vehicles in China, the outage of vehicles with different battery types is analyzed here. As can be seen from Figure 2, ternary and lithium iron phosphate batteries occupy the mainstream, and are close to the overall outage rate of 10% and 13% respectively, while supercapacitors are special, and the outage rate of assembled vehicles is zero. After investigation and analysis, the related vehicles are converted into light-duty vehicles after the users can remove the batteries, and the service life is long.

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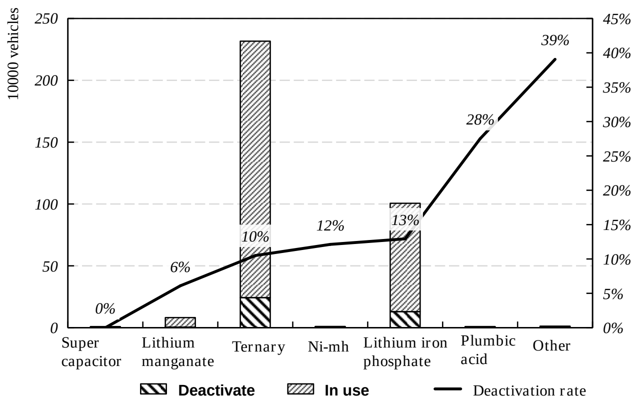

Figure 2: Deactivation rate of vehicles with different battery types

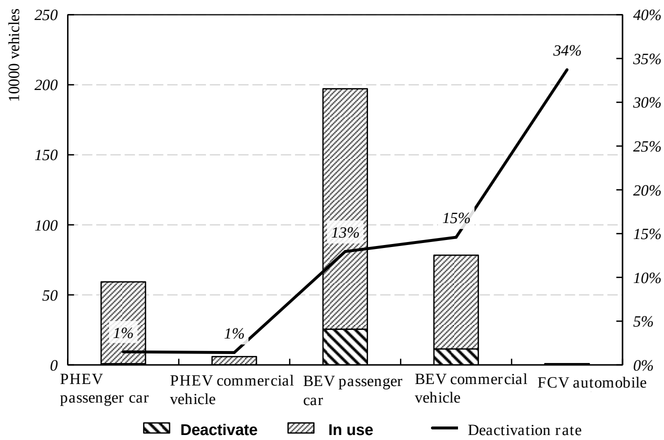

Figure 3: Vehicle deactivation rate for different vehicle types

According to the vehicle type, the outage rate is analyzed, and the results are shown in Figure 3. It can be found that there are significant differences among different types of vehicles. Plug-in hybrid vehicles (PHEV) have a low outage rate, which is 1% for both passenger cars and commercial vehicles. Pure electric vehicles (BEV) have a relatively high outage rate, which is 13% and 15% for passenger cars and commercial vehicles respectively. Fuel cell vehicles have the highest outage rate of 35%, but it accounts for a small proportion of data.

3. Model building

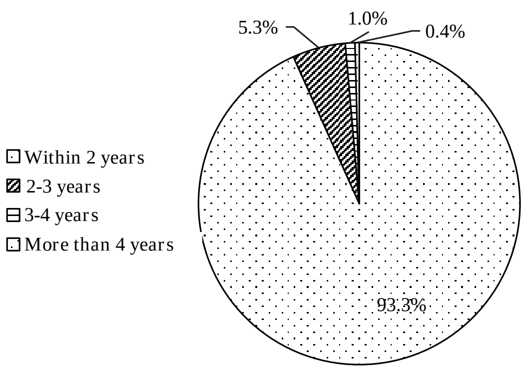

Figure 4: Vehicle situation of different vehicle types

To refine the data and build the model, we analyzed the difference of production time of different models, as shown in Figure 4. 93.3% of the models have a production year span of no more than 2 years, and about 98.6% have a production year span of no more than 3 years. According to the actual product development cycle, the rate of technical generation difference of the same model product is very low. In

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order to study the outage rate curve of each vehicle type conveniently, this paper assumes that the quality of the same vehicle type is similar, and the outage rate distribution curve is consistent. Based on this assumption, the vehicle service month, the corresponding number of vehicles and the number of vehicles out of service are calculated for each vehicle type, which is used to construct the Weibull distribution model.

(1) Model building

The probability distribution formula and cumulative probability distribution formula of Weibull distribution are as follows:

$$f(x)=\begin{cases}\frac{k}{\lambda}\left(\frac{x-\gamma}{\lambda}\right)^{k-1}e^{-\left(\frac{x-\gamma}{\lambda}\right)^{k}} & x\geq 0\\ 0 & x<0\end{cases} \tag{1}$$

Its cumulative distribution function is:

$$F(x)=\begin{cases}1-e^{-\left(\frac{x-\gamma}{\lambda}\right)^{k}} & x\geq 0\\ 0 & x<0\end{cases} \tag{2}$$

The median point of its cumulative distribution function is:

$$E=\lambda(\ln 2)^{1/k}+\gamma \tag{3}$$

It can be seen that the median point is negatively correlated with λ value. Because the median point is greater than 1 in this problem, E is negatively correlated with the shape parameter K.

Its cumulative distribution function F(x) can be changed as follows:

$$[(x-\gamma)/\lambda]k=-\ln(1-F(x))$$

$$\ln(x-\gamma)=\ln\{-\ln(1-F(x))\}/k+\ln(\lambda)$$

$$\ln\{-\ln(1-F(x))\} = k\cdot\ln(x-\gamma)-k\cdot\ln(\lambda)$$

$$(F(x)\in(0,1))$$

It can be considered that there is a linear correlation between ln(x-γ) and ln{-ln(1-F(x))}, and the γ of the three-parameter Weibull distribution generally takes the shortest time of failure, which is 13 (i.e. 390 days) here. The deactivation rate of some corresponding models in the month is 0% or 100%. In order to avoid losing information or causing big errors, the point with the ratio of 0% is discarded here, and the point with the ratio of 100% is changed to 99.99% to improve the fitting degree of the second half of the function.

Because the retired data fitting needs a certain amount of data, it is restricted here that the vehicle models with only 4 data points or less will not be fitted separately. For this type of vehicle, the deactivation rate follows the comprehensive model of the corresponding battery type and vehicle type. By calculating the parameters of each vehicle type respectively, the outage rate model of all new energy vehicles can be constructed. Where n is the total number of vehicle models, $N_{\text{production}}$, λ and K are all

$$N_{\text{retire}}=\sum_{i}^{n}N_{\text{production}\,i}\cdot(1-e^{-(x/\lambda_i)^{k_i}}) \tag{4}$$

Through calculation, the fitted K and λ values of 1651 vehicle types, 3 battery types (ternary, Ferrous lithium phosphate, others) and 5 vehicle types (pure electric passenger cars, pure electric commercial vehicles, plug-in hybrid passenger cars, plug-in hybrid commercial vehicles and fuel cell vehicles) are obtained, as shown in Table 1. It can be seen that the R^2 of ternary plug-in hybrid commercial vehicle and ternary pure electric commercial vehicle is low, and the fitting degree is low, which indicates that there are other main influencing parameters in these two types of vehicles. Here, it is not calculated according to the general category, but only the parameters of the specific vehicle type. For the data that cannot be solved, it is not predicted here.

Based on the analysis of vehicle types, the linear fitting R^2 of 845 vehicles exceeds 0.8, which

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indicates that the decommissioning rate of these vehicles is strongly correlated with the duration of use, accounting for 51% of the total number of vehicles. The fitting R^2 of 1482 vehicles exceeds 0.5, accounting for 90% of the total number of vehicles, which shows that, on the whole, there is a certain correlation between the decommissioning rate and the usage time of the vehicle data with fitting conditions, as shown in Figure 5.

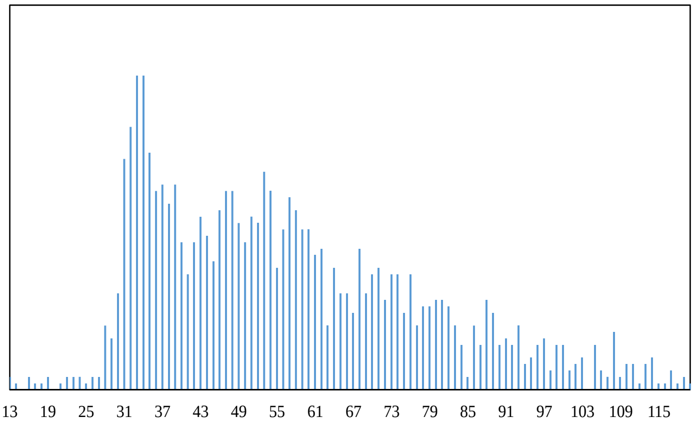

Figure 5: Monthly distribution of the median monthly cumulative probability of deactivation of various models

Table 1: Parameter fitting of various battery vehicle types

Battery type	**Vehicle type**	**Shape factor k**	**Scale factor λ**	**R^2**	**Median E**
Ternary	Pure electric passenger car	3.607	59.74	78.1%	67.0
Ternary	Plug-in hybrid passenger car	3.499	105.87	80.2%	108.3
Ternary	Pure electric commercial vehicle	1.553	114.78	24.5%	103.7
Ternary	Plug-in hybrid commercial vehicle	1.112	1906.98	6.3%	1384.6
Ternary	Fuel cell vehicle	8.515	23.07	58.6%	35.1
Lithium iron phosphate	Pure electric passenger car	3.121	78.61	80.6%	82.9
Lithium iron phosphate	Pure electric commercial vehicle	2.016	96.90	47.5%	93.8
Lithium iron phosphate	Plug-in hybrid passenger car	5.112	91.67	90.3%	98.3
Lithium iron phosphate	Plug-in hybrid commercial vehicle	2.786	172.47	48.5%	164.2
Other	Pure electric passenger car	2.600	103.20	70.1%	102.6
Other	Pure electric commercial vehicle	2.084	113.45	68.2%	108.2
Other	Plug-in hybrid commercial vehicle	2.570	233.51	58.0%	215.5
Other	Fuel cell vehicle	6.963	26.11	60.6%	37.8

This method can be used to effectively distinguish and predict the vehicle types that have the trend of centralized deactivation. The result of fitting according to the model. It can be seen that all models are retired in 3-6 years. It can also be clearly found that the expectation of the decommissioning rate of different vehicles is scattered, and there will be a big error in predicting the decommissioning distribution based on the industry average.

4. Distribution prediction of decommissioning volume

By using the calculated and analyzed decommissioning models of each vehicle type, we can predict and study the decommissioning area distribution of power batteries in the future. Based on the available data, 47,000 vehicles except ternary commercial vehicles and Ferrous lithium phosphate fuel cell vehicles for which corresponding parameters have not been calculated, and 380,000 vehicles that have been stopped, are excluded from the total of 4.13 million vehicles. The data of the remaining 3.678 million vehicles is increased by 365 days, so as to predict the expectation of new vehicles stopping service in the whole country one year later. According to the division of provinces and cities, the expected distribution of new power battery decommissioning areas in each province and city from July 2020 to June 2021 is obtained in Table 2.

By analyzing the distribution of expected battery decommissioning, it can be seen that there is

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regional imbalance in the distribution of power battery decommissioning. Guangdong, Shandong, Zhejiang, Henan, Jiangsu and other provinces occupy the top five, while municipalities such as Shanghai, Beijing and Tianjin are expected to stop using more than 10,000 vehicles in one year. The relevant data can be used to directly realize the regional distribution analysis of decommissioning quantity at the prefecture level.

Table 2: 2020.07-2021.06 Regional distribution of new energy vehicles deactivate

Disabled vehicle province	Stop usage expectation
Guangdong	30036
Shandong	23081
Zhejiang	23075
Henan	20944
Jiangsu	19541
Hebei	18399
Shanghai	17128
Beijing	15716
Tianjin	14722
Sichuan	13370
Hubei	12331
Shanxi	12102
Hunan	11885
Fujian	11634
Anhui	11350
Shaanxi	11011
Other provinces	67223
Total	333548

5. Conclusions

Based on the terminal data of new energy vehicles, this paper uses Weibull distribution as the distribution model of vehicle outage rate for data analysis. It is found that the outage rate and service time of new energy vehicles can be analyzed by Weibull distribution, and more than 90% of the data are correlated. In this paper, the one-year distribution of new energy vehicles' decommissioning is further realized, and the prediction and analysis of battery decommissioning quantity can be accurately carried out by vehicle type and battery type to the city, which provides a theoretical basis for further industry layout planning. The model designed in this study can be iterated, has good interpretability, and can be used to quantitatively analyze and observe the risk of battery batch decommissioning in the industry, support the judgment of the competent government departments, and help related enterprises to make industrial layout.

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