Forecasting the Retirement Quantity of Power Batteries in Henan Province for Recycling Logistics Network Optimization

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Abstract. Under the "dual carbon" goals, rapid growth of the new energy vehicle (NEV) industry has increased end-of-life (EoL) power batteries, posing challenges for recycling logistics. Accurate retirement forecasting is essential for optimizing network layout and resource allocation. Using NEV sales data in Henan Province from 2017 to 2024, a Grey GM(1,1) model is applied to forecast sales from 2025 to 2030, and installed battery capacity is estimated accordingly. Considering battery lifespan distribution, the Stanford model is used to predict the scale and temporal evolution of retirement. To improve robustness, scenario-based interval estimation and sensitivity analysis are introduced. Results show that retired battery volume will continue to grow and enter a concentrated release phase, peaking around 2032 with clear lag and phased characteristics. These findings support recycling node layout, transportation optimization, and capacity planning, and provide a reference for regional recycling system development and reverse logistics network design.

Keywords: Power battery recycling; Grey GM(1,1) model; Stanford model

1 Introduction

Driven by carbon neutrality goals and energy transition, China's new energy vehicle (NEV) industry has expanded rapidly, leading to a growing number of end-of-life (EoL) power batteries. Accurate forecasting of battery retirement is therefore essential for recycling system planning.

Forecasting NEV market size provides an important basis for estimating future battery retirement [1]. The Grey GM(1,1) model has been widely used in forecasting problems with small samples due to its adaptability [2]. Existing studies have further improved GM(1,1) to enhance prediction accuracy for non-exponential data [3].

In terms of battery retirement estimation, life cycle–based approaches such as the Weibull distribution are commonly applied [4]. The Stanford model combines historical sales data with lifetime distribution to estimate end-of-life quantities over time [5]. Based on retirement forecasts, some studies have also analyzed the carbon footprint of

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battery reuse and recycling [6]. In addition, deep learning methods have been introduced to predict battery remaining useful life with high accuracy [7].

Existing studies have advanced NEV forecasting and battery retirement estimation, but mainly focus on national-level analysis, with limited regional research. This study focuses on Henan Province, applying the GM(1,1) model to forecast NEV sales and the Stanford model to estimate battery retirement.However, these studies often lack uncertainty analysis, explicit lifetime distribution specification, and direct linkage to logistics network optimization. To address these gaps, this study incorporates uncertainty quantification and sensitivity analysis, explicitly defines lifetime distribution, and links forecasting results to recycling logistics network planning.

2 Research Methods

2.1 Grey GM(1,1) Forecasting

The GM(1,1) model is suitable for forecasting systems with limited and incomplete data. Given the relatively small sample size of NEV sales data, it is adopted in this study for short-term prediction.

Let the original data sequence be $X^{(0)}=\{x^{(0)}(1),x^{(0)}(2),\ldots,x^{(0)}(n)\}$ After the accumulated generating operation (AGO), the sequence becomes $X^{(1)}$. The GM(1,1) model can be expressed as:

$$\frac{dx^{(1)}}{dt}+ax^{(1)}=b$$

where a is the development coefficient and b is the grey input. The time response function is

$$x^{(1)}(k+1)=\left(x^{(0)}(1)-\frac{b}{a}\right)e^{-ak}+\frac{b}{a}$$

The predicted values of the original sequence can be obtained through inverse AGO.

The model is used to forecast NEV sales. Compared with ARIMA and logistic growth models, GM(1,1) is more suitable for small-sample conditions, although multi-model validation can be explored in future research.

2.2 Stanford Model

The Stanford model estimates end-of-life (EoL) volume based on sales and lifetime distribution.

Let the sales volume in year t be S_t, and the lifetime distribution be $f(i)$, where i denotes service life. The EoL volume in year t is:

$$W_t=\sum_{i=1}^{n} S_{t-i}\cdot f(i)$$

where W_t is the retired battery volume in year t; $S_{t\text{-}i}$ is the sales in year t-i; $f(i)$ is the probability of retirement after i years; and n is the maximum service life.

Battery lifespan ranges from 5 to 8 years and is modeled using a discrete distribution.The lifetime distribution is explicitly defined as: f(5)=0.1, f(6)=0.2, f(7)=0.4, f(8)=0.3, indicating that most batteries retire during years 6–7.

The Stanford model has been widely applied in retirement forecasting because it explicitly considers the time lag between product sales and end-of-life generation. Rather than assuming a fixed service life, the model estimates retirement quantities by combining historical sales with a lifetime probability distribution, thereby reflecting the gradual release of retired batteries over time. In this study, the adopted discrete lifetime distribution is consistent with the commonly reported service life of lithium-ion power batteries under normal operating conditions. This probabilistic treatment allows the retirement process to better represent actual market conditions and improves the realism of long-term forecasting results.

2.3 Method for Calculating Power Battery Retirement Volume

NEV sales are converted into battery mass for retirement estimation. Battery mass typically ranges from 0.3–0.7 t per vehicle, and the midpoint is adopted as the average battery weight. To evaluate the robustness of this assumption, sensitivity analysis is conducted using 0.3 t, 0.5 t, and 0.7 t per vehicle. Results show that while absolute retirement volumes vary, the overall trend and peak timing remain stable.

$$\beta = 0.5\mathrm{t} \cdot veh^{-1}$$

Let NEV sales in year t be N_t. The installed battery volume is:

$$B_t = N_t \times \beta$$

where B_t is the installed battery volume, N_t is NEV sales, and β is the average battery weight per vehicle.

Retirement volume is calculated as:

$$W_t = \sum_{i=1}^{n} \mathrm{B}_{t\text{-}i} \cdot f(i)$$

This method predicts future battery retirement volumes.

2.4 Uncertainty Analysis

To account for uncertainty in forecasting, a scenario-based interval estimation is adopted. A ±10% variation is applied to baseline results to represent conservative and optimistic scenarios.

The interval estimation does not attempt to predict all possible uncertainties but provides a practical range for evaluating future retirement volumes under different development conditions. Such uncertainty analysis is particularly valuable for recycling logistics planning because infrastructure investment and processing capacity decisions should consider not only baseline demand but also potential fluctuations. The interval results therefore provide decision-makers with additional flexibility when determining facility scale and resource allocation strategies.

3 Empirical Analysis

3.1 New Energy Vehicle Sales Data and GM(1,1) Forecasting

Based on Henan Province's new energy vehicle sales data from 2017 to 2025 (Table1), the Grey GM(1,1) model was used to forecast future sales. During the modeling process, the original data did not pass the level-ratio test; therefore, it was processed using a shift transformation to meet the model construction requirements.

Table 1. New Energy Vehicle Sales in Henan Province, 2017–2025

Year	2017	2018	2019	2020	2021	2022	2023	2024	2025
Sales (10,000 units)	4.10	7.16	3.99	8.62	23.31	32.22	50.09	68.00	85.00

The model calculations yielded the development coefficient $a=-0.1034$ and the grey influence$b=67.4882$. Further model accuracy tests were conducted, yielding a posterior deviation ratio of $C=0.0288$ and a small error probability of $p=1.000$. According to the grey model accuracy evaluation criteria,$C<0.35$ and $p>0.95$, indicating that the model's accuracy grade is “Excellent,” and the prediction results possess high reliability.

Based on this, NEV sales for 2026–2030 were forecasted, with numerical results shown in Table 2.

Table 2. Forecast Values for New Energy Vehicle Sales, 2026–2030

Year	2026	2027	2028	2029	2030
Sales (Volume)	99.80	119.93	142.25	167.01	194.46

The gray GM(1,1) model is more suitable for short-term forecasting, and forecasting errors may accumulate over time. Additionally, due to limitations in the length of the sample data, this paper sets the forecast period for new energy vehicle sales to 2030.

3.2 Stanford Model Forecast of Power Battery Retirement Volume

Since the service life is 5–8 years, battery retirement exhibits a lag relative to sales. To capture this lag, the retirement forecast is extended to 2035 based on NEV sales forecasts through 2030.Based on GM(1,1) forecasts and an average battery weight of 0.5 t/vehicle, NEV sales are converted into installed capacity as input for the Stanford model, with the results presented in Table 3.

Table 3. Forecast of Power Battery Retirement Volume in Henan Province

Year	2026	2027	2028	2029	2030	2031	2032	2033	2034	2035
Retired units (10,000 tons)	3.90 (3.51–4.29)	6.26 (5.63–6.89)	11.68 (10.51–12.85)	18.35 (16.52–20.19)	25.90 (23.31–28.49)	34.60 (31.14–38.06)	43.18 (38.86–47.50)	51.82 (46.64–57.00)	61.53 (55.38–67.68)	72.86 (65.57–80.15)

Early deployed batteries entered a concentrated retirement phase around 2024-2025. The results show clear phased characteristics: retirement remains low during 2026–2028, increases steadily after 2029 as earlier NEVs retire, peaks around 2032, and then gradually declines.

Sensitivity analysis indicates that although absolute values vary under different assumptions, the overall evolution pattern remains consistent.

The forecast results reveal a gradual transition from the initial accumulation stage to a period of rapid retirement growth. This evolution reflects the combined influence of continuously increasing NEV sales and the delayed retirement characteristics of power batteries. As the large number of vehicles sold after 2020 gradually reach the end of their service life, battery retirement is expected to increase substantially, resulting in higher collection and transportation demand throughout the province. Consequently, recycling enterprises should prepare for this concentrated retirement period by expanding collection capacity, improving transportation efficiency, and optimizing the spatial allocation of recycling facilities.

From the perspective of recycling logistics network optimization, the forecasted retirement trend provides important quantitative information for long-term infrastructure planning. Regions with rapidly increasing retirement quantities may require additional collection stations or temporary storage facilities to reduce transportation costs and improve operational efficiency. Furthermore, processing facilities should reserve sufficient treatment capacity before the retirement peak arrives in order to avoid resource shortages and operational bottlenecks. These findings indicate that retirement forecasting can effectively support strategic decision-making throughout the entire recycling logistics system.

4 Conclusions and Recommendations

This study focuses on Henan Province. Using NEV sales data from 2017 to 2025, a Grey GM(1,1) model is applied to forecast future NEV development, and the Stanford model is used to estimate battery retirement based on lifespan distribution.To improve model robustness, uncertainty analysis and parameter sensitivity are incorporated in this study.

Results indicate that NEV sales maintain sustained growth driven by policy and market demand, while battery retirement exhibits a clear time lag due to the 5–8 year lifespan, evolving from accumulation to concentrated release. The retirement volume follows a phased pattern, transitioning from low levels to rapid growth, peaking and then declining. Overall, retirement dynamics are governed by NEV growth and life-cycle effects, forming a “growth–lag–release” pattern.Sensitivity analysis shows that although absolute values vary under different assumptions, the overall evolution trend and peak timing remain stable.

These results provide direct quantitative support for recycling logistics network optimization, including facility capacity planning, node location decisions, and transportation demand estimation. For example, the peak retirement around 2032 implies the need for maximum processing capacity and expanded collection networks during that period.

Although the proposed approach provides an effective framework for regional retirement forecasting, several aspects deserve further investigation. Future research may compare the forecasting performance of the Grey GM(1,1) model with other forecasting approaches using longer time series as additional data become available. Moreover, retirement forecasts can be integrated with geographic information systems and multi-objective optimization models to determine optimal locations for recycling facilities while simultaneously minimizing transportation costs and carbon emissions. Further improvements may also include dynamic updates of battery lifetime distributions based on technological advances and user behavior, thereby enhancing the long-term reliability of retirement forecasting and recycling logistics network planning.

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