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RESEARCH ARTICLE

Cascade Use or Recycle? Secondary Life Planning for Electric Vehicle Batteries in China

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ABSTRACT: China's electric vehicle (EV) industry has experienced rapid growth in recent years, becoming a significant driver of economic and technological advancements. Lifecycle management of EV batteries is now a pressing issue due to environmental concerns. This paper investigates this problem, focusing on the dual strategy of recycling and cascade utilization. Using extensive real-world data, models are estimated to predict EV batteries' performance and lifespan under practical conditions. These capacity degradation models are then applied to forecast the future growth of EV and non-electric vehicle (non-EV) battery volumes and the capacity structure of the battery population. Furthermore, a mathematical model is formulated to describe the flow of batteries in the EV and non-EV population, capturing EV battery transitions through cascade utilization to non-EV uses and to recycling. An optimization problem is then proposed to maximize social utility and to guide decisions on cascade utilization.

KEYWORDS: Environmental Engineering, Recycling and Waste Management, Electric Vehicle Batteries, Management Science.

Introduction

Over the past five years, Electric Vehicles (EVs) have seen rapid growth globally. In 2024, EV sales exceeded 17 million, accounting for over 20% of all vehicle sales. The European Union, the United States, and China remain the three major markets, and Asia and Latin America are important emerging markets that see rapid growth in EV sales.[1]

The forecast for 2025 shows that EV sales are expected to grow further to exceed 20 million worldwide. The driving force for such growth varies in different markets. For example, in China, it is policy incentives, such as a trade-in scheme where higher rebate is offered for the purchase of an EV purchase than that the purchase of a conventional vehicle, as well as infrastructure development, and domestic manufacturing capacity, that will push share of EV sales up to 60%; in Europe, it is the emission reduction target that will drive up the shares of zero-emission EVs to 25%; and in the United States, sales are projected to raise slightly to 11% due to change in policy direction.[2]

Driven mostly by the increase in EV sales, in 2024, battery production that satisfies both EV demand and storage applications reached the 1TWh milestone. China remains the largest source of demand at 60% of global demand, European Union and the United States at 13%.[2]

Recognizing these international differences, this paper focuses on the Chinese context, examining optimal recycling and cascade utilization strategies tailored to its unique market conditions and policy environment.

Beyond economic benefits, the widespread adoption of EVs also brings substantial environmental advantages. Electrification of transportation is seen as a pivotal strategy to reduce dependence on petroleum-based fuels and to mitigate urban air pollution.[3] EVs, with zero tailpipe emissions, contribute to improved air quality and reduced greenhouse gas emissions when powered by low-carbon energy sources.

However, the rapid expansion of the EV market also brings new challenges, particularly in the management of retired batteries. With the rapid development of EVs, the number of retired batteries is expected to surge in the coming years. According to Wu *et al.*,[4] the volume of retired power batteries is projected to rise from 112,000 tonnes in 2020 to 708,000 tonnes by 2030. The substantial increase in retired batteries underscores the urgent need for efficient reuse and recycling strategies. Improper disposal of batteries can lead to severe environmental and safety risks. For instance, leaked heavy metals from improperly disposed batteries can contaminate water and soil, and pose threats to ecosystems and human health through bioaccumulation in the food chain.[5] Additionally, improper dismantling of EV batteries could pose significant safety concerns, such as fire or explosion.[6]

Typically, there are two main strategies for handling retired EV batteries: recycling and cascade utilization. Recycling involves dismantling batteries to reclaim valuable materials such as lithium, cobalt, and nickel, which can be used to manufacture new batteries. In other words, recycling aims to convert power batteries into various raw materials with minimal pollution. Cascade utilization, on the other hand, repurposes batteries for secondary applications after their initial use as EV batteries. This strategy extends the lifecycle of EV batteries and mitigates the environmental impact of battery disposal. Cascade utilization includes applications in energy storage systems,[7] backup for base stations,[8] grid support services,[9] and renewable energy integration,[10] etc. According to the report by the China Electricity Council,[11] from 2019 to 2022, storage demand grew from 466 MWh to 5,498 MWh for renewable energy stations, from 523 MWh to 1,812 MWh for the power network, and from 119 MWh to 758 MWh for commercial demand. The rapid growth demonstrates the potential need for cascade-utilized EV batteries.

While recycling is a straightforward solution, it fails to fully harness the capacity of EV batteries. From the perspective of social welfare, cascade utilization is a superior strategy as it enables maximal utilization of battery capacities. However, the proper planning, management, and operations of cascade utilization remain challenging.

In this paper, we analyze and explore issues related to the life cycle management of EV batteries, including: when to recycle and when to cascade utilize? How to balance the two strategies? How to develop them in the long term?

We first investigate the capacity degradation pattern for individual batteries to lay the foundation for our study. The modeling utilizes two publicly available datasets to provide insights into the typical lifespan and performance decline of EV batteries. The analysis is then extended from individual batteries to the entire battery population, depicting its capacity distribution at any point in time. A cascade utilization flow model is introduced to capture the transition of batteries from EV to non-Electric Vehicle (non-EV) markets, and their eventual flow to recyclers. Based on the current state of the EV and the cascade utilization market, we project future growth in battery volumes. It shows that the number of retired EV batteries will be enormous, with only a small fraction absorbed by the current cascade utilization market, thus highlighting a significant underutilization of this potential strategy.

In summary, this paper provides a quantitative analysis of the economic and policy factors influencing the cascade utilization of EV batteries. Through detailed modeling of battery degradation patterns, market projections, and the effects of government subsidies, this paper aims to inform and guide policymakers and industry stakeholders in making strategic decisions that enhance the sustainability and economic viability of EV battery lifecycle management.

Literature Review

The related literature mainly consists of research in two areas: the pattern of battery capacity degradation and multi-party relationships related to the recycling of batteries.

Capacity Degradation of Batteries:

Battery capacity degradation is a significant concern for the sustainability and performance of EVs. Different approaches have been used in modeling battery degradation. The first is by simulating the underlying physical degradation mechanisms. Edge *et al*. provide a comprehensive overview of lithium-ion battery degradation mechanisms.[12] They discuss the coupling between different degradation processes and propose a semi-empirical model that integrates physical and chemical degradation mechanisms. This model aims to predict capacity fade and enhance battery management systems. Luo *et al*. present a detailed study on capacity degradation and aging mechanisms in lithium-ion batteries under various operating conditions.[13] Their empirical model considers factors such as the solid electrolyte interphase (SEI) growth, lithium plating, and particle cracking to predict battery lifespan under different depths of discharge and temperatures.

Another approach is to employ data-driven methods to model the degradation process of batteries. Zhang *et al*. built an accurate battery forecasting system based on electrochemical impedance spectroscopy.[14] A Gaussian process model takes the entire collected spectrum as input and automatically determines which spectral features better predict degradation. Huang *et al*. propose a novel charging encoder that alternates between a Temporal Convolutional Network and a Bidirectional Gated Recurrent Unit to capture local temporal information and long-term dependencies related to the state of capacity (SOC) and the state of health (SOH) during charging.[15] The proposed framework enables a unified joint estimation of the two variables, substantially enhancing efficiency.

Recycling of EV Batteries:

As the battery recycling and cascade utilization market expands, more research efforts start to focus on the decision-making relationship between the various parties in this context.

Some of them focus on the strategy analysis of different roles in the supply chain, including pricing, contracts, and benefit distribution. Gu *et al*. propose a closed-loop supply chain model in which EV batteries can be reused, such as for energy storage, before being recycled.[16] They analyze the optimal pricing strategy between the manufacturer and remanufacturer to optimize the total profit in the whole supply chain. Zhu and Yu study the effect of adverse selection and moral hazards in the closed-loop supply chain of EV batteries based on Information Screening Models in the principal-agent theory.[17]

Some papers examine the impact of government policies. Gu *et al*. look for the optimal production strategy when market demand is uncertain under government subsidy.[18] It is concluded that the optimal production quantity and expected utility increase with the subsidy. Guan and Hou study the equilibrium strategy of the EV battery supply chain under the dual mechanism of government subsidy and cost-sharing and find that the utility of cascade utilization efforts will increase with the increase of government subsidies.[19]

In this paper, the focus is not on the benefits and decisions of participants at the micro level; instead, it focuses on the circulation of batteries from a macro perspective and hopes to optimize social welfare through macro-control measures such as cascade utilization standards.

Methods

Electric Vehicle Battery Capacity Degradation Model:

To develop effective recycling and cascade utilization strategies, it is essential to understand the mechanisms behind the capacity degradation of EV batteries over time. In this section, we propose an EV battery capacity degradation model to help accurately predict their lifespan and performance under real-world conditions.

Battery capacity refers to the total amount of electric charge a battery can store, quantified as a real number and measured in ampere-hours (Ah). Generally, a larger battery capacity allows for more energy storage, enabling EVs to travel greater distances on a single charge. It serves as a crucial indicator of a battery's health status, with higher values representing better overall performance.

The performance of EV batteries inevitably degrades with increased usage. This degradation is primarily reflected in the gradual decline of battery capacity. Over time, this reduction in capacity diminishes the battery's ability to store and deliver energy effectively. This degradation also forms the basis for cascade utilization. As EV batteries degrade over time, they eventually become unsuitable as power batteries but retain value for other applications. The timing of their retirement is critical to determining their remaining utility in secondary applications.

To characterize the overall condition of EV batteries, it is necessary to accurately describe the capacity degradation of EV batteries. Some studies have examined the performance of batteries under laboratory conditions. However, in real-world scenarios, the use of EV batteries is far more complex than under laboratory testing conditions. EV batteries are affected by numerous complex real-world factors, such as unstable voltage, random charging times, EV owners' charging preferences (charging only when nearly depleted or frequent partial charging), constantly changing ambient temperature, and more. These factors can render the battery degradation curves obtained under laboratory conditions invalid.

Therefore, to accurately model the capacity degradation of EV batteries, it is essential to build the model with extensive real-world data, which ultimately helps capture the most fundamental degradation pattern.

In our study, two publicly available EV battery datasets are utilized to model the degradation curve and perform corresponding statistical analysis. Both datasets comprise parameters of EV batteries under real-world conditions.

Dataset A provides long-term charging data from 20 commercial EVs with identical battery systems, each monitored over approximately 29 months.[20] The data were collected during charging via CAN communication at regular intervals and captured key patterns relevant to real-world battery health evaluation. The metric for battery usage is the length of time in service, which is reasonable given that commercial EVs are in continuous operation.

Dataset B offers a large-scale time-series capacity data of 191 EVs, including over 1.2 million charging sessions from vehicles across three manufacturers.[21] Each session records multiple charging-related parameters at fixed intervals, including voltage, current, temperature, capacity, and estimated SOC. The dataset is designed to facilitate deep learning research on charging behavior, battery degradation, safety, and energy management in real-world settings. The usage metric in this dataset is the odometer reading.

In both datasets, each EV has an average of over 2,000 data points of battery capacity. An overview of these datasets is shown in Table 1.

Table 1: Overview of two EV battery datasets: dataset A from 20 commercial EVs monitored over approximately 29 months, dataset B from 191 EVs with over 1.2 million charging sessions.

Dataset	#EVs	#Avg. Points per EV	#Total Points	Usage Metric
Dataset A[20]	20	~2,696	53,927	Time in service (day)
Dataset B[21]	191	~3,068	585,922	mileage (km)

Let C denote the capacity of EV batteries, and x denote the usage metric. A two-step process is used to investigate the relationship between C and x. First, the correlation coefficient between C and x is calculated to check if their correlation is indeed negative, as intuitively expected. The linear regression model is then estimated:

$$C = \beta\, x + \alpha \tag{1}$$

Table 2: Correlation and linear regression analysis between battery capacity C and usage metrics x. A strong negative correlation is found in both datasets. The linear regression models are $C = -2.228 \times 10^{-2} * \textit{Time in Service} + 132.573$ for Dataset A, and $C = -2.554 \times 10^{-5} * \textit{Mileage} + 43.308$ for Dataset B.

Dataset	Correlation between C and x	Parameter	Estimate	95% Confidence Interval
Dataset A	−0.709	β	-2.228×10^{-2} *	[-2.247×10^{-2}, -2.209×10^{-2}]
		α	132.573 *	[132.475, 132.671]
Dataset B	−0.695	β	-2.554×10^{-5} *	[-2.561×10^{-5}, -2.548×10^{-5}]
		α	43.308 *	[43.301, 43.315]

Notes: * indicates significance at the $p < 0.001$ level.

The following observations are made based on the results shown in Table 2:

(1) C and x exhibit a strong negative correlation in both datasets (−0.709 for Dataset A and −0.695 for Dataset B), consistent with the well-known fact that battery capacity decreases with increased usage.

(2) Recall the substantial differences between the two datasets in terms of battery types, EV models, data collection conditions, and usage metrics. Note that both datasets result in correlation coefficients close to −0.7, which indicates that the rate of battery capacity degradation with usage is consistent.

(3) Data points contain much noise, highlighting the difficulty of accurately predicting battery capacity at the individual level under real-world conditions. The considerable noise may be attributed to complex environmental factors that lead to a wide range of data fluctuations. This suggests that a large number of samples (data points) is necessary to effectively mitigate the impact of noise on parameter estimation.

(4) The 95% confidence intervals for the parameters are very narrow, indicating a low degree of uncertainty in the parameter estimates. We also show the curve fitting of Datasets A and B in Figures 1 and 2, respectively.

DOI: 10.36838/v8i2.50

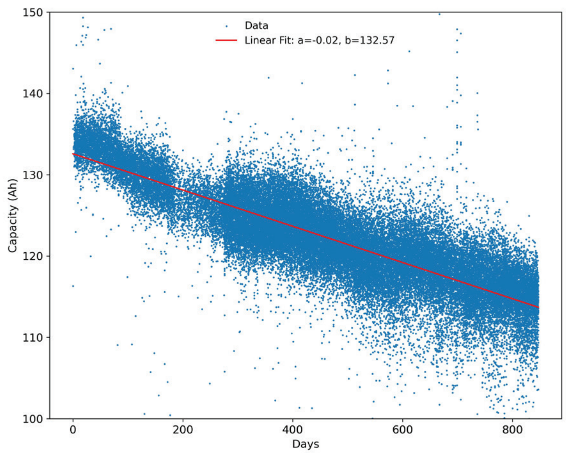


Figure 1: Battery capacity vs number of days in service in Dataset A: scatter plot in blue and linear regression line $C = -2.228 \times 10^{-2} * \textit{Time in Service} + 132.573$ in red.

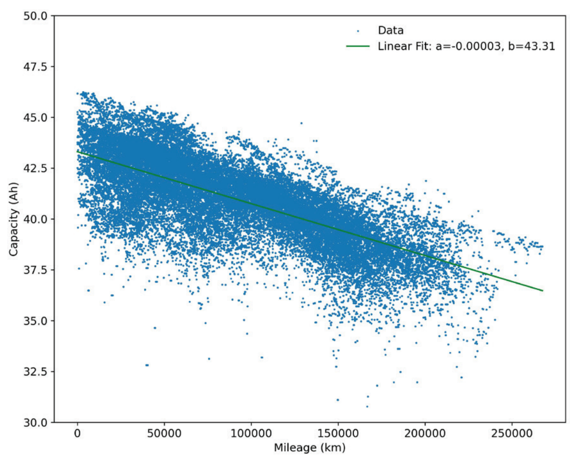


Figure 2: Battery capacity vs mileage in Dataset B: scatter plot in blue and linear regression line $C = -2.554 \times 10^{-5} * \textit{Mileage} + 43.308$ in dark green.

It is observed from Figures 1 and 2 that the capacity of EV batteries decreases linearly with increased usage. These linear models form the basis for our discussion on the cascade utilization flow model in the next section.

Optimization of Cascade Utilization for Social Welfare:

This subsection explores how the government could manage the cascade utilization to maximize social welfare. The following notations are used in subsequent discussions.

$D_t^{(EV)}$ and $D_t^{(Non\text{-}EV)}$: demand for batteries by the EV and non-EV population at time step t, respectively.

$B_t^{(EV)}$ and $B_t^{(Non\text{-}EV)}$: the number of new batteries that need to be produced for the EV and non-EV population at time step t, respectively.

$I_t^{(EV)}$ and $I_t^{(Non\text{-}EV)}$: the number of batteries in the EV and non-EV population at time step t, respectively.

$I_{t,c}^{(EV)}$ and $I_{t,c}^{(Non\text{-}EV)}$: the number of batteries with capacity c in the EV and non-EV population at time step t, respectively.

$r_t^{(EV)}$ and $r_t^{(Non\text{-}EV)}$: the number of batteries to be recycled from the EV and non-EV population at time step t, respectively.

s_t: the number of batteries cascaded from the EV population to the non-EV population at time step t.

Figure 3 illustrates the flow of EV and non-EV batteries. The demand for EV batteries ($D_t^{(EV)}$), is satisfied by batteries that are currently in the EV population and the number of new batteries produced ($B_t^{(EV)}$). Due to capacity degradation, batteries will no longer meet the capacity requirements of the EV population after a period of usage. Some ($r_t^{(EV)}$) need to be directly recycled, while others (s_t) still hold value for cascade utilization in the non-EV population. Therefore, demand for non-EV batteries ($D_t^{(Non\text{-}EV)}$), is satisfied by current batteries in the non-EV population, new production for non-EV usage ($B_t^{(Non\text{-}EV)}$), and batteries cascaded from the EV population (s_t). Batteries in the non-EV population also degrade, and some need to be recycled ($r_t^{(Non\text{-}EV)}$). By knowing the state at each timestamp, the evolution of the battery population can be captured starting from $t = 0$ onward.

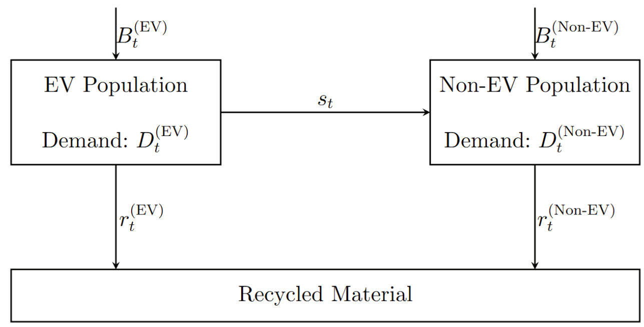


Figure 3: Flow of batteries in the market at time step t. The demand for EV batteries ($D_t^{(EV)}$) is satisfied by batteries that are currently in the EV population and the number of new batteries produced ($D_t^{(EV)}$). Demand for non-EV batteries ($D_t^{(Non\text{-}EV)}$) is satisfied by current batteries in the non-EV population, new production for non-EV usage ($B_t^{(Non\text{-}EV)}$), and batteries cascade utilized from the EV population (s_t). Some batteries ($r_t^{(EV)}$, $r_t^{(Non\text{-}EV)}$) are recycled.

In the process of cascade utilization of EV batteries, government intervention is often necessary to maximize social welfare. Government policies and regulations can provide essential guidelines for the proper management of battery resources, ensure environmental protection, and promote sustainable economic development. A better understanding of the dynamics between cascade utilization and recycling of batteries will guide more effective government policies.

Let c_0 denote the initial capacity of a battery, and c_R the recycling threshold for EV batteries. Similarly, c_S is the threshold for cascade utilization, and $c_S > c_R$. For all EV batteries with a capacity of c_S, we stipulate that no more than a proportion q of them will be cascade utilized, while the rest will continue to be used in the EV market until they are recycled. In this process, the initial capacity c_0 and recycle capacity c_R are determined by the characteristics of batteries, while the cascade capacity c_S and cascade ratio q can be adjusted by the government. These standards can directly affect the flow of batteries, including production, supply, utilization, and recycling. Therefore, we want to explore how the standards should be developed to enhance the overall societal benefits.

Battery Dynamics in the EV Population:

The batteries used in the EV population gradually degrade in daily driving and end up in the non-EV population or are recycled. To accurately model the battery flow in the EV population, let δc be the capacity degraded during one time step, and $I_{t,c}^{(EV)}$ be the number of batteries with capacity c at time step t. At each time step t, the number of batteries with capacity c_0 in the EV population is equal to the number of batteries produced for the EV population at time step t:

$$I_{t,c_0}^{(EV)} = B_t^{(EV)} \tag{2}$$

The batteries with capacity $c_S + \delta c$ in the EV population will degrade to capacity c_S, which is the capacity threshold for cascade utilization. Considering that not all batteries can be collected for cascade utilization, we assume only a proportion q of them can be transferred into the non-EV population. Furthermore, the demand for new non-EV batteries also restricts the number of batteries transferred. Therefore, the batteries transferred from the EV population to the non-EV population can be expressed as:

$$s_t = \min\{I_{t,c_S+\delta c}^{(EV)} \cdot q, \max\{0, D_t^{(Non-EV)} - I_t^{(Non-EV)}\}\} \tag{3}$$

and the number of batteries with capacity c_S in the EV population at time step $t + 1$ is equal to the number of batteries that are not transferred into the non-EV population,

$$I_{t+1,c_S}^{(EV)} = I_{t,c_S+\delta c}^{(EV)} - s_t \tag{4}$$

When batteries with capacity $c_R + \delta c$ degraded to c_R, they are forced to be recycled,

$$r_t^{(EV)} = I_{t,c_R+\delta c}^{(EV)} \tag{5}$$

Then, the number of batteries with capacity c_R in the EV population at time step t becomes 0,

$$I_{t,c_R}^{(EV)} = 0 \tag{6}$$

For batteries in other capacity ranges, the number of batteries with capacity c in the EV population at time $t + 1$ is equal to the number of batteries with capacity $c + \delta c$ in EV users at time step t. To be specific, this applies to the capacity ranges $c_S + \delta c \leq c \leq c_0 - \delta c$ and $c_R + \delta c \leq c \leq c_S - \delta c$. This degradation process can be expressed as:

$$I_{t+1,c}^{(EV)} = I_{t,c+\delta c}^{(EV)}, \text{for } c_S + \delta c \leq c \leq c_0 - \delta c \text{ and } c_R + \delta c \leq c \leq c_S - \delta c \tag{7}$$

At time step t, the total number of batteries in EV users $I_t^{(EV)}$ is the sum of the batteries with capacities ranging from c_R to c_0:

$$I_t^{(EV)} = \sum_{c=c_R}^{c_0} I_{t,c}^{(EV)} \tag{8}$$

Then for each time step t, the total number of batteries in EV users at time step t should be no less than the battery demand of the EV population at time step t:

$$I_t^{(EV)} \geq D_t^{(EV)} \tag{9}$$

Equivalently, the number of batteries produced for the EV population can be expressed as:

$$B_t^{(EV)} = \max\{D_t^{(EV)} - I_t^{(EV)}, 0\} \tag{10}$$

Battery Dynamics in the Non-EV Population:

The batteries used in the non-EV population are either batteries produced for non-EV usage or are from the EV population. Non-EV batteries can be used for energy storage and power supply for communication base stations, power stations, and in other commercial settings. These batteries will also gradually degrade over time and end up being recycled. We assume that they follow the same degradation pattern as the EV batteries. Similar to the modeling of the EV population, let $I_t^{(Non-EV)}$ be the number of batteries in the non-EV population with capacity c at time step t, and δc be the capacity degraded within one time step. The number of batteries with capacity c_0 in the non-EV population at time t is equal to the number of batteries produced for the non-EV population at time step t,

$$I_{t,c_0}^{(Non-EV)} = B_t^{(Non-EV)} \tag{11}$$

The number of batteries with capacity c_S at time step $t + 1$ is equal to the number of batteries with capacity $c_S + \delta c$ at time step t plus the number of batteries transferred from the EV population s_t,

$$I_{t+1,c_S}^{(Non-EV)} = I_{t,c_S+\delta c}^{(Non-EV)} + s_t \tag{12}$$

When batteries with capacity $c_R + \delta c$ degraded to the standard non-EV battery recycle capacity c_R, they are recycled,

$$r_t^{(Non-EV)} = I_{t,c_R+\delta c}^{(Non-EV)} \tag{13}$$

The number of batteries with capacity c_R at time step t is 0, indicating that all batteries of this capacity are recycled,

$$I_{t,c_R}^{(Non-EV)} = 0 \tag{14}$$

Batteries of other capacities follow a normal degradation, which means that the number of batteries with capacity c at time $t + 1$ is equal to the number of batteries with capacity $c + \delta c$ at time t,

$$I_{t+1,c}^{(Non-EV)} = I_{t,c+\delta c}^{(Non-EV)}, \text{for } c_S + \delta c \leq c \leq c_0 - \delta c \text{ and } c_R + \delta c \leq c \leq c_S - \delta c \tag{15}$$

At time step t, the total number of batteries $I_t^{(Non-EV)}$ is the sum of the batteries with capacities ranging from c_R to c_0,

$$I_t^{(Non-EV)} = \sum_{c=c_R}^{c_0} I_{t,c}^{(Non-EV)} \tag{16}$$

DOI: 10.36838/v8i2.50

The total number of batteries at time step t should be able to cover the demand for batteries at time step t,

$$I_t^{(Non-EV)} \geq D_t^{(Non-EV)} \tag{17}$$

Equivalently, the batteries to be produced for the non-EV population can be expressed as

$$B_t^{(Non-EV)} = \max\{D_t^{(Non-EV)} - I_t^{(Non-EV)} - s_t, 0\} \tag{18}$$

Social Welfare Modeling:

With the formulation of the battery dynamics in the EV and non-EV population, we further formulate the social welfare of this process. In this context, social welfare is the benefits that battery usage brings to society. For example, using EV batteries with higher average capacity can improve the overall efficiency of EV usage, thereby enhancing the efficiency of the entire transportation system and contributing to greater social welfare. Conversely, lower capacity reduces efficiency, leading to lower social welfare. We assume the social welfare brought by the batteries used in the EV and non-EV populations is related to the mean capacity in each population. The mean capacities can be calculated as:

$$c_t^{(EV)} = \sum_{c=c_R}^{c_0} I_{t,c}^{(EV)} \, c / I_t^{(EV)} \tag{19}$$

$$c_t^{(Non-EV)} = \sum_{c=c_R}^{c_0} I_{t,c}^{(Non-EV)} \, c / I_t^{(Non-EV)} \tag{20}$$

We use a utility function $f^{(EV)}$ to characterize the social welfare within the EV population. For EV owners, when the degradation starts from a brand-new battery, the major effect is the gradual reduction in range. However, as battery capacity continues to degrade, some other issues become more apparent, including deterioration in acceleration and braking performance, slowing down of charging speeds, and a greater failure rate of the vehicle's information systems.[22] Therefore, we propose to employ a non-linear utility function $f^{(EV)}$ of mean EV capacity to measure the unit social welfare of the EV population:

$$f^{(EV)}(c) = \begin{cases} k_1(c - c_R), \text{if } c_R \leq c < c^{EV} \\ k_1(c^{EV} - c_R) + k_2(c - c^{EV}), \text{if } c^{EV} \leq c \leq c_0 \end{cases} \tag{21}$$

where $k_2 < k_1$ are the slopes for the piece-wise linear utility function, and c^{EV} is the threshold where the slope changes. Similarly, the unit social welfare of the non-EV population can also be measured by a non-linear function:

$$f^{(Non-EV)}(c) = \begin{cases} k_3(c - c_R), \text{if } c_R \leq c < c^{Non-EV} \\ k_3(c^{Non-EV} - c_R) + k_4(c - c^{Non-EV}), \text{if } c^{Non-EV} \leq c \leq c_0 \end{cases} \tag{22}$$

where $k_4 < k_3$ are slopes of the utility function $f^{(Non-EV)}$, and c^{Non-EV} is the threshold where the slope changes. The non-EV population often has lower requirements on batteries; therefore, it is reasonable to assume that $c^{Non-EV} < c^{EV}$ and $k_4(c^{Non-EV} - c_R) \geq k_1(c^{EV} - c_R)$.

Based on the unit social welfare and the battery ownership in the EV and non-EV population, their total social welfare can be respectively expressed as:

$$u_t^{(EV)} = f^{(EV)}\left(c_t^{(EV)}\right) \cdot I_t^{(EV)} \tag{23}$$

$$u_t^{(Non-EV)} = f^{(Non-EV)}\left(c_t^{(Non-EV)}\right) \cdot I_t^{(Non-EV)} \tag{24}$$

We assume that new batteries are manufactured with unit cost c_m. With the number of batteries produced for both EV and non-EV populations, the related social welfare at time step t is $- c_m\,(B_t^{(EV)} + B_t^{(Non-EV)})$.

To make EV batteries available for non-EV utilization, the following costs must be considered.[23] First, the batteries need to be dismantled, which requires labor and equipment costs. Before entering the non-EV population, batteries need to be inspected to determine if they meet the non-EV utilization standards based on their remaining life and performance. Batteries may also need to be repackaged or remanufactured before entering the cascade utilization market to ensure safe transportation and storage. We denote the unit transfer cost by k_s, which covers all the costs mentioned above, and the related social welfare in time step t can be expressed as $- k_s\, s_t$.

For recycling end-of-life batteries, there are also several costs to be considered. The end-of-life batteries often need to be centralized for further processing because of the potential hazards and pollution that can result from the process. Therefore, the logistics cost incurred during battery collection and transportation is not negligible. The collected end-of-life batteries also need to be sorted and pre-processed, which means labor costs, the cost of sorting equipment, and the cost of preliminary discharge and disassembly of batteries. Then these batteries are processed using chemical, mechanical, and thermal treatment methods, which incur costs for equipment usage, chemical reagents, energy consumption, and labor. These processes are often accompanied by useless or even harmful by-products, like waste liquids, residues, and gases. The cost of handling those hazardous substances should also be considered. In our formulation, we denote the unit battery recycle cost by kr to account for all the costs mentioned above in the recycling process. Since the batteries can be recycled from the EV and non-EV population, the related social welfare at time step t is expressed as $- k_r\,(r_t^{(EV)} + r_t^{(Non-EV)})$.

Based on the above formulation of the EV and non-EV battery dynamics and social welfare, the decision-making of the government can be advised by the following optimization problem:

$$\max_{c_S, q} \frac{1}{T} \sum_t u_t^{(EV)} + u_t^{(Non-EV)} - k_s s_t - k_r\left(r_t^{(EV)} + r_t^{(Non-EV)}\right) - c_m\left(B_t^{(EV)} + B_t^{(Non-EV)}\right) \tag{25}$$

Subject to: EV battery dynamics in Eqs. (2-8), and (10),
Non-EV battery dynamics in Eqs. (11-16), and (18),
Capacity calculation in Eqs. (19) and (20).

Social welfare ($u_t^{(EV)}$, $u_t^{(Non-EV)}$) is calculated using Eqs (23) and (24). Recall that the parameter q is the maximum cascade ratio of batteries, and the actual number of batteries that can be transferred to the non-EV population is also restricted by the demand of the non-EV population. Intuitively speaking, a lower q limits the cascade utilization of batteries. Therefore, if a battery can bring more social utility after entering the non-EV population, the total social welfare would increase with q. On the other hand, if a battery can bring more social utility when staying in the EV population, the total social welfare may decrease with a larger q, because a smaller q can keep more batteries in the EV population and result in more social welfare.

The effect of c_S is much more complex. From the perspective of the life cycle of an individual battery, the manufacturing cost and the recycling cost are fixed and not influenced by c_S. If the battery stays in the EV population until recycled, social welfare is not influenced by c_S. If a battery is transferred to the non-EV population at capacity c_S, a higher c_S generates greater social welfare in the non-EV population compared to the EV population, as indicated by our formulation of the functions $f^{(EV)}(c)$ and $f^{(Non\text{-}EV)}(c)$, along with the associated parameter requirements. If the difference in social welfare between the EV and non-EV population exceeds the transfer cost ks, the more batteries transferred, the more social welfare is achieved. A higher c_S means a battery can serve for a longer time in the non-EV population until recycled, which lowers the demand of the non-EV population, and results in a reduction in the volume of batteries transferred. In addition, a higher c_S may also accelerate the replacement of batteries in the EV population, which incurs more cost for the production of new batteries. These effects we discussed are also highly dependent on the parameter settings and the real-world demand and capacity distribution. Therefore, the overall effect of c_S is hard to predict.

Model Assumptions and Limitations:

Before we discuss computational results, it should be noted that several assumptions are made in this study. First, the battery degradation model assumes linear capacity degradation, which may differ from actual nonlinear degradation patterns influenced by varying operational conditions. Second, the battery population is treated as homogeneous despite variations in battery chemistries and usage scenarios. Finally, our predictions rely on logistic growth modeling of market demand, which may not fully capture market uncertainties or disruptive technological changes. These limitations should be considered when interpreting the results.

Result and Discussion

Estimated Growth of EV and Non-EV Batteries:

We collected data on EV ownership in the Chinese market from 2017 to 2023.[24] Based on this data, we estimate the future growth of the EV market. Three models are selected for this estimation: the exponential model, the quadratic function model, and the logistic growth model, with mean squared error (MSE) used as the evaluation metric. Figure 4 shows the fitting performance of these three models, with time in the horizontal axis, where a real-valued interval $[i, i+1)$ represents Year i, and the number of EVs in the vertical axis.

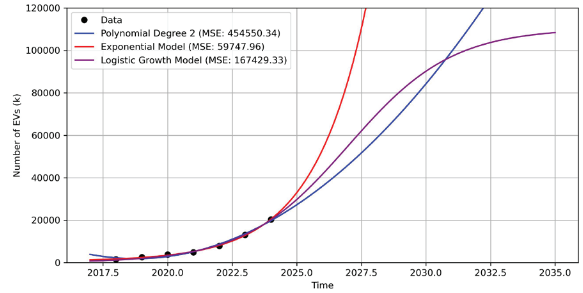


Figure 4: Estimate of EV growth in China based on data from 2017-2023. Three models - exponential, quadratic function, and logistic growth – are estimated. Mean squared error (MSE) for each model is included as a measure of fitness. Since future growth cannot increase indefinitely as predicted in the exponential model and the quadratic function model, the logistic growth model is selected as the preferred model.

Although the exponential model provides the best fit for the 2017-2023 data, it should be noted that using it to predict future growth could be problematic since the number of EVs cannot grow indefinitely as predicted in the exponential model and the quadratic function model. Furthermore, the logistic growth model exhibits low fitting errors, indicating a decent fit. It is also noteworthy that, according to our proposed model, EV ownership will reach approximately 100 million by the end of 2030. This prediction aligns with the forecast made by leading experts, which underscores the validity and reliability of our proposed model.[25]

According to EVChina, the most common cascade uses of EV batteries are for energy storage in communication base stations, renewable energy storage, and public facility energy storage.[26] We aggregate the demand data for these three applications from 2018 to 2022 to obtain the overall demand data for the cascade use. Based on the data, we fit a logistic growth model for the demand of non-EV batteries (note that this amount is calculated based on the capacity of EV batteries). Figure 5 shows the fitting result. It can be observed that the scale of electricity usage for these non-EV batteries experiences a period of rapid growth, followed by a slowdown in growth, and eventually stabilizes around 2035.

The estimated numbers of EV and non-EV batteries are used as the initial conditions, $D_1^{(EV)}$ and $D_1^{(Non\text{-}EV)}$, in the cascade flow model.

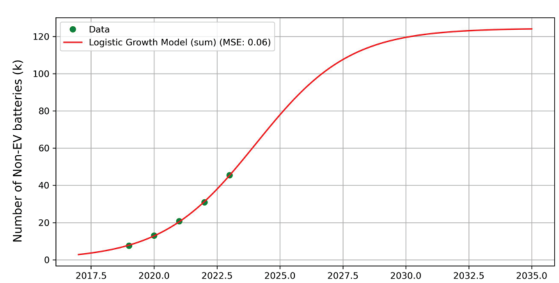


Figure 5: Logistic growth curve for non-EV batteries in China. The logistic growth model is estimated using data from 2018-2022 that cover energy storage in communication base stations, renewable storage, and public facility storage.

DOI: 10.36838/v8i2.50

Macro Perspective on Cascade Utilization Flow Model:

The evolution of battery population is simulated using the flow model, including EV battery dynamics in Eqs. (2-8), and (10), non-EV battery dynamics in Eqs. (11-16), and (18), and capacity calculation in Eqs. (19) and (20). The corresponding social welfare ($u_t^{(EV)}$, $u_t^{(Non\text{-}EV)}$) is calculated using Eqs. (23-25).

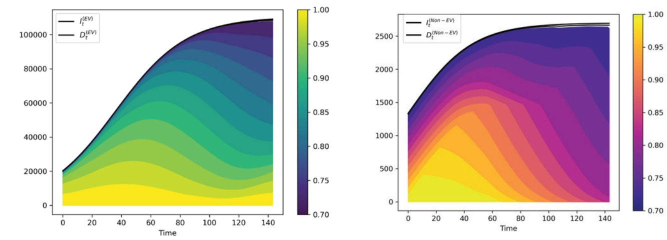
The parameter settings for the simulation study are listed in Table 3. More specifically, the parameters for time are based on our defined study period, parameters for battery degradation are from the empirical analysis discussed in the Electric Vehicle Battery Capacity Degradation Model section of this paper, cost-related parameters are adopted using a normalization approach based on the conceptual frameworks in related studies,[18,19] and the social utility parameters are based on the key contribution of our model, designed to capture the proposed non-linear welfare effects of battery performance.[18]

Table 3: Parameter settings for the cascade utilization flow model. The battery population evolution is simulated for 12 years (144 time steps; each time step is a month).

Parameters	Values
T	144 (12 years)
k_s	0.3
k_r	0.01
c_m	1
c_0	1
δc	1 / 480
c^{EV}	0.8
k_1	8
k_2	1
$c^{Non\text{-}EV}$	0.8
k_3	40
k_4	5 / 7

Figure 6 shows the total number of batteries, as well as the changes in battery capacity structure. We partition the capacity value of [0.7, 1] into 12 equal intervals and mark intervals with different colors. For EV batteries, the ratio of batteries of high capacity (capacity 0.85 ~ 1) will first increase and then decrease. This is because the number of EV batteries will initially undergo a rapid growth phase, during which a large number of new batteries with high capacity will enter the population, increasing their proportion. As growth slows, the number of new batteries entering the population each period will decrease. Additionally, the capacity of batteries from the previous high-growth phase will gradually degrade, leading to an increase in the proportion of low-capacity batteries (capacity 0.7 ~ 0.85).

In the initial phase (time step 1 to 40), the proportion of high-density batteries in non-EVs is rising. This is because there are too few EV batteries available for cascade utilization to meet the non-EV demand at this stage. Consequently, additional new batteries need to be produced for non-EV applications. These high-capacity new batteries increase their proportion in the population. After this initial phase, the overall capacity within the non-EV population rapidly declines. By the end of the simulation, almost all non-EV batteries originate from the cascade utilization of EV batteries. This shift is due to the rapid growth in EV batteries, which significantly increases the number of EV batteries available for cascade utilization, adequately meeting the non-EV electricity demand.



(a)EV batteries (b) Non - EV batteries

Figure 6: Change in EV and non-EV battery populations and their capacity distributions over time. The capacity range [0.7, 1] is divided into 12 equal intervals, represented by different colors. In the EV battery population, the proportion of high capacity (capacity > 0.85) batteries will increase initially and then decrease, proportion of low capacity (capacity between 0.7 and 0.85) batteries will increase due to capacity degradation over time. In the non-EV population, after an initial phase with a high proportion of high-capacity batteries, the overall capacity rapidly declines.

Deeper Analysis of Cascade Utilization Dynamics:

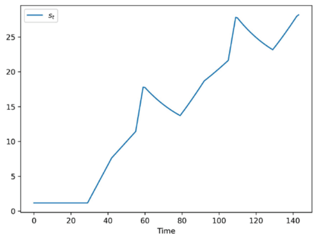
In Figure 7, other key variables in the model are presented to better understand the dynamics of cascade utilization.

• The number of EV batteries for cascade utilization, st, remains close to zero during the period from $t = 0$ to $t = 30$, after which it begins to increase. This initial phase sees a scarcity of EV batteries suitable for cascade utilization. However, as the scale of EV batteries rapidly grows, each period witnesses a substantial number of EV batteries degrading to the capacity threshold c_S, making them available for cascade utilization and leading to the subsequent increase in s_t.

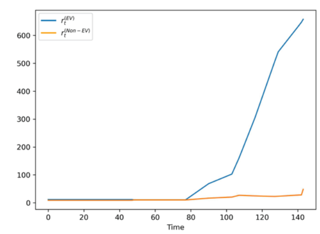
• Both $r_t^{(EV)}$ and $r_t^{(Non\text{-}EV)}$, the numbers of batteries recycled from the EV and non-EV populations, have a rapid increase after t = 70. This is due to both market demands experiencing rapid growth phases, with these batteries gradually retiring after 5 to 10 years of use, leading to a significant increase in r_t. This also warns us that if we cannot effectively manage the impact of retired batteries, our environment will be severely polluted by the chemical elements contained in these retired batteries.

• The production of EV batteries each period $B_t^{(EV)}$ exhibits three phases: an initial increase, followed by a decrease, and then another increase. The trends in the first and second phases are due to the rapid initial growth rate of required EV batteries, which then slows down. The increase in the third phase is attributed to the large number of batteries retiring from earlier periods, necessitating the production of new EV batteries to meet this demand.

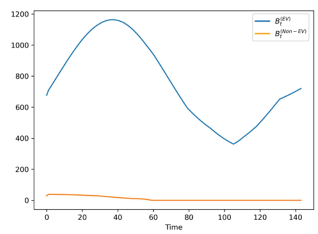
• The average capacity of non-EV batteries initially increases briefly and then continues to decline. This is because, in the early stages, non-EV batteries require new batteries to meet rapidly increasing demand. As the scale of EVs expands and the number of EV batteries available for cascade utilization increases, the non-EV battery demand can be adequately met by these cascade-utilized EV batteries, leading to a continuous decrease in average capacity.



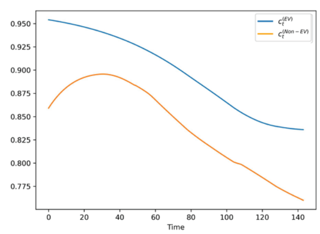
(a) Number of cascade utilization batteries, s_t. It remains close to zero till t = 30, then begins to increase substantially.



(b) Number of recycled batteries from EV and non-EV population, $r_t^{(EV)}$ and $r_t^{(Non\text{-}EV)}$. Both increase rapidly after t = 70 because batteries retire after 5 to 10 years of use.



(c) Battery production for EV and non-EV, $B_t^{(EV)}$ and $B_t^{(Non\text{-}EV)}$. $B_t^{(EV)}$ experiences a rapid initial increase to meet the demand, followed by a decrease, and then another increase when the initial batteries retire and more new ones need to be produced.



(d) Average capacity of EV and non-EV population, $c_t^{(EV)}$ and $c_t^{(Non\text{-}EV)}$. $c_t^{(Non\text{-}EV)}$ increases briefly and then continues to decline. This is because the initial demand for non-EV is satisfied by new batteries but later the demand can be adequately met by cascade utilized batteries.

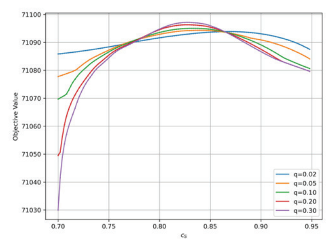
Figure 7: Key variables in the cascade utilization flow model.

Sensitivity Analysis of Key Parameters:

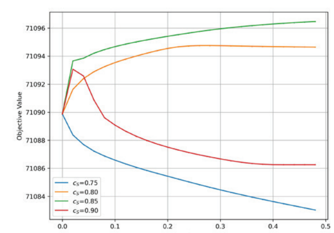
To maximize the objective function of social welfare, we need to understand at what capacity level (c_S) and in what proportion (q) EV batteries should be cascade utilized. We analyze the changes in the objective function under two scenarios: (1) varying c_S while keeping q constant, and (2) varying q while keeping c_S constant. Figure 8 shows the results from the two scenarios.

• Varying c_S with fixed q. At different levels of q, we vary c_S from 0.7 to 0.95, covering a large range of battery capacity. The curves in Figure 8(a) consistently exhibit an increase followed by a decrease as cS increases. This trend is due to the trade-off between EV and non-EV batteries. If c_S is low, the number of EV batteries that need to be produced each period is reduced, which lowers the cost of producing new EV batteries. However, the average capacity of batteries available for cascade utilization will also be lower, resulting in lower social welfare for the non-EV sector. Conversely, if c_S is high, the average capacity of EV batteries will increase social welfare in the EV sector, but more EV batteries will need to be produced. The batteries available for cascade utilization will have a higher average capacity, thereby increasing the social welfare in the non-EV sector. These factors interact, ultimately leading to an objective function curve that initially increases and then decreases. This also implies that, for a fixed level of q, there exists an optimal value for c_S somewhere between c_R and c_0.

• Varying q with fixed c_S. Intuitively, we believe that a higher proportion of batteries available for cascade utilization can increase the objective function. However, our results as shown in Figure 8(b) indicate that this intuition only holds true when the value of c_S is appropriate. If the value of c_S is too low (that is, close to the mandatory recycling level c_R), then the average capacity of the cascade utilized batteries will be low. Therefore, increasing q will result in the non-EV population being flooded with nearly obsolete batteries, causing a decline in the objective function. On the other hand, if the value of c_S is too high, then batteries are utilized for cascade applications early in their life cycle, and significantly more EV batteries will need to be produced each period, again leading to a decline in the objective function. Only when the value of c_S is appropriate -- the battery performance is no longer sufficient to meet the requirements of EV usage but can still satisfy the needs of cascade utilization -- will increasing q lead to a continuous increase in the objective function.



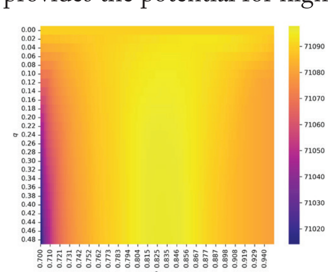
(a) Social utility as a function of c_S, capacity level for cascade use. For a fixed level of q, there exists an optimal value for c_S that maximizes social welfare.



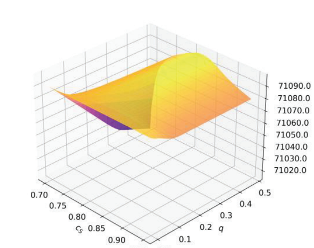
(b) Social utility as a function of q, proportion of EV batteries that could be utilized for cascade use.

Figure 8: Social utility as a function of c_S and q.

To visualize how the objective function is affected by both c_S and q simultaneously, we show the variations in the objective function values on a parameter grid, as shown in Figure 9. The parameter grid is spanned by q = [0, 0.5) with interval 0.02 and c_S = [0.7, 0.95) with interval δc, and the maximum value is attained when q = 0.48 and c_S = 0.829. It is conceivable that if we continue to increase the value of q, the objective may still have minor increases, because increasing q means increasing the number of batteries available for cascade utilization, which provides the potential for higher social welfare.



(a) 2D Heatmap of objective values on parameter grids.



(b) 3D Heatmap of objective values on parameter grids.

Figure 9: Heatmap of objective values on parameter grids of c_S and q. Parameter q ranges from 0 to 0.5, and parameter c_S from 0.7 to 0.95. The maximum objective value is attained when q = 0.48 and c_S = 0.829.

DOI: 10.36838/v8i2.50

Conclusion

This paper presents a comprehensive analysis of the lifecycle management of EV batteries, emphasizing the dual strategies of recycling and cascade utilization. By leveraging extensive real-world data, we developed a model that predicts battery lifespan and performance, providing a robust foundation for policy and strategic decisions. The alignment of our model's predictions from a macro market perspective with expert forecasts[23] underscores the validity and reliability of the model and demonstrates its practical applicability in real-world scenarios. This model also forms the basis for subsequent analyses.

Sensitivity analysis of key parameters is conducted to identify the most impactful factors on system performance. This analysis reveals the importance of optimizing the cascade ratio and recycling efficiency to maximize social welfare. Policymakers should consider these findings when formatting regulations and incentives to ensure they address the most critical aspects of battery lifecycle management.

The following recommendations, derived from numerical findings and analysis, provide a roadmap for policymakers to enhance the sustainability and economic viability of EV battery lifecycle management.

1. Enhancing data collection and sharing: Governments should promote the establishment of comprehensive databases for battery usage and degradation data. This would improve model accuracy and enable better lifecycle management of EV batteries.

2. Establishing robust recycling standards: Implementing strict recycling standards can ensure that retired batteries are processed in an environmentally friendly manner, minimizing hazardous waste and promoting the recovery of valuable materials.

3. Supporting technological innovation: Investing in research and development for advanced battery technologies and recycling processes can drive innovation, improve recycling efficiency, and reduce costs. This includes supporting the development of more efficient battery degradation models.

4. Developing infrastructure for battery management: Building robust infrastructure for the collection, transportation, and processing of batteries is essential. This includes creating facilities for recycling and cascade utilization to ensure efficient handling of retired batteries.

5. Monitoring the advancements in battery technology: Adjustments to policy decisions regarding cascading utilization should be made in response to changes in the patterns of battery capacity degradation, based on the prevailing circumstances.

In conclusion, this study provides insights for policymakers and industry stakeholders and presents a path forward for improving the sustainability and economic viability of EV batteries. Future research should continue to refine and expand to more complicated battery degradation models, to incorporate emerging data, and to explore new strategies to further enhance EV battery management. By doing so, we can ensure that the rapid growth of the EV industry contributes positively to both economic development and environmental sustainability.

Acknowledgments

I would like to thank my research mentor, Dr. Dazhou Lei, for his patience, guidance, and support throughout the research process.

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DOI: 10.36838/v8i2.50