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Research Article

Reverse Logistics Network Design of Electric Vehicle Batteries considering Recall Risk

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In 2018-2019, the recall scale of electric vehicles (EVs) in China reached 168,700 units; recalls account for approximately 6.9% of sales volume. There are imperative reasons for electric vehicle batteries (EVBs) recalls, such as mandatory laws or policies, safety and environmental pollution risks, and the high value of EVB echelon use, and thus, it has become increasingly important to reasonably design a reverse logistics (RL) network for an EVB recall. In this study, a multiobjective and multiperiod recall RL network model is developed to minimize safety and environmental risks, maximize the social responsibility and economic benefits, and consider the characteristics of EVBs, including the configuration of key recall facilities and the control of recall flows. The results of this study will help EVB practitioners, relevant departmental policymakers, and others to comprehensively understand the recall of EVBs, strengthen the safety and environmental protection issues in the EVB recall process, and promote the establishment of a safe, green, and sustainable EVB recall RL network.

1. Introduction

According to the International Energy Agency [1], global EV ownership exceeded 7.2 million units by the end of 2019, and the annual sales of EVs are predicted to reach 80 million units by 2030 in the context of sustainable development. A report released by China's General Administration of State Market Regulation [2] shows that 168,700 EVs were recalled in 2018-2019; recalls account for approximately 6.9% of sales volume. China's Ministry of Industry and Information Technology released a report on the Big Data Safety and Supervision Achievements of the National Supervision Platform for EVs [3], which showed that, from May to August 2019, 58% of vehicles burned, where the cause of the fire was identified, were due to battery problems. Defective EVBs, product recalls, and accidents are common to current RL process triggers [4]. EVBs are different from ordinary products, and there are certain safety hazards in EVBs. There are serious environmental pollution hazards from the leakage of EVBs [5]. Therefore, their safety, environmental protection, and whether they can be effectively recalled and disposed of are also a wide concern. In the event of an emergency recall owing to safety or environmental concerns, it is even more important to establish a fast and safe RL network.

This study considers the safety risks of EVB recall such as spontaneous combustion and explosion as well as environmental pollution risks such as liquid leakage and corrosion and establishes an RL network for new energy vehicle EVBs based on recall risks. The aim of this study is to solve the optimization problem of network site selection during this safe and green recall process.

Firstly, this study constructs an RL network for EVB recall. This network includes service outlet, recall site, recall processing center, recall transfer center, and echelon use center. Second, based on fitting the existing data and predicting the possible recall of EVBs in the next three years, this study establishes a multiobjective and multiperiod recall RL network site selection model, which aims at minimizing safety and environmental risks and maximizing social responsibility and economic benefits.

In the study, the network considers innovation indicators such as testing cost, packaging cost, and recall time of EVBs, considers economic indicators such as transportation

cost and storage cost, and considers social responsibility indicators such as employment opportunities. Finally, we determine the appropriate location and flow in the recall RL network.

The contributions of this study are as follows: (1) factor characteristics of EVB recalls, the costs of a safety risk detection and packaging when considering the potential environmental contamination, and job growth in terms of social responsibility are considered, (2) a mixed-integer nonlinear programming (MINLP) model with the goal of minimizing safety and environmental risks and maximizing social responsibility and economic benefits is established, and (3) sensitivity analysis is performed. The analysis examines the weighting of safety and environmental protection, social responsibility, and economic benefit and argues that the economic gains made are meaningful only if safety and environmental protection are ensured and that only by coordinating safety and environmental protection with economic benefits can we encourage the sustainable development of an EVB recall RL network.

The remainder of this paper is organized as follows. Section 2 provides a brief review of the related literature. The methodology employed in this study is described in Section 3. Assumptions and formulas are presented in Section 4. Section 5 describes an empirical study conducted on the RL network of Shanghai's EVB recall when considering the risk of such a recall. Finally, Section 6 provides some concluding remarks and discusses the limitations of this research.

2. Literature Review

A review of the concept and development of RL: Stock [6] first proposed the concept of RL, which is broadly defined to include all logistics activities related to resource conservation, recycling, replacement, reuse of materials, and disposal. To address the social sustainability of RL, Sarkis et al. [7] studied RL from the triple bottom line of economic, environmental, and social benefits and established sustainability indicators related to various RL practices. Whereas RL has been considered a cost for companies in the past, Hao et al. [8] argued that, in the global trend of the green low-carbon cycle, RL is an important way for companies to generate additional profits. Thus, Wang et al. [9] found that improving the efficiency of end-of-life EV RL is an important way to promote green development and social benefits. Alamerew and Brissaud [4] expanded the thinking regarding RL, moving from a resource-efficient model to a fully circular and sustainable model.

In the study on RL network design, Fleischmann et al. [10] summarized the common features of RL networks, studied the location of RL network facilities and inventory management, and conducted a quantitative study of RL decision models. Barros et al. [11], Min et al. [12], Zhou and Cao [13], and Zaarour [14] all proposed MINLP models and considered using heuristic algorithms to optimize them. Governments have also started to gradually pay attention to the development of RL, and Zhou et al. [15] constructed a multiperiod multiobjective dynamic MINLP model by optimizing the social cost, economic cost, and recovery revenue based on government subsidies and solved it using the particle swarm algorithm. The green environment has been an integral part of a logistics network design; in forward logistics, Zhen [16] developed a multiperiod green supply chain network and established the dual-objective model with the aim of minimizing total supply chain costs and carbon emission; in RL, Govindan et al. [17], Trochu et al. [18], and Nageswara et al. [19] took environmental policy requirements, pollution reduction, and carbon emission reduction into consideration to develop a rational RL network and established the MINLP model. Most recent studies have used the MINLP method to model RL networks, and increasing focus has been given to green and low-carbon issues in the models; however, to date, little attention has been paid to safety.

Regarding the optimization of an EVB RL network, Hoyer et al. [20] developed a strategic framework for the design of recycling networks for waste lithium-ion batteries of EVs. Hao et al. [21] evaluated the feasibility of RL of end-of-life vehicle batteries based on an improved fuzzy neural network. EVBs are different from ordinary products. Huo et al. [22] argued that EVBs have certain corrosive, flammable, explosive, and toxic properties, and the unregulated recycling and disposal of EVBs may lead to fire, explosion, and pollution of the environment. In addition to the recall of EVBs, which has certain safety risks, Sloop et al. [23] studied the recall of lithium batteries and found that batteries can create a useful value after recall. Based on ecological, economic, and geostrategic reasons, Hakim et al. [24] designed a sustainable recycling network for lithium batteries under uncertainty and developed recycling network modeling and value chain solutions to match batteries. Wang et al. [25] argued the need for end-of-life lithium battery recycling management and the establishment of a sound end-of-life lithium battery infrastructure to reduce the uncertainty of RL and maximize the use of battery recycling to reduce economic costs. Jayant et al. [26] proposed a predictive approach that can calculate the battery collection costs, transfer time, transfer costs, and resource utilization and designed and developed a simulation model of an RL network using the example of waste battery collection in Sangrur District of northern India. In addition, Hendrickson [27] combined a life cycle assessment and GIS to analyze how the energy, greenhouse gas, water, and standards of a lithium-ion battery end-of-life infrastructure network affect air pollutants and determined the optimal location of battery disassembly and recycling facilities for use in a California recycling program. Tadaros et al. [28] proposed a discrete multiperiod facility location allocation RL MINLP model to address the recycling of EVBs from EVs in Sweden. In addition, Masudin et al. [29] developed an RL network for battery recycling from the end customer to the remanufacturing process from the perspectives of environment and transportation costs. Wang et al. [30] developed an "Internet+" battery recycling system with a reward and punishment mechanism to solve the problem of recycling end-of-life batteries. From the above studies, it can be seen that many approaches have taken cost reduction, environmental issues, and uncertainty into consideration when designing

EVB RL networks, and most have adopted the MINLP model as a solution.

A product recall is an important element of RL [31]. However, there have been few studies on recall RL network optimization. Jayaraman et al. [32] established an RL network for product recycling, product recall, product disposal, and hazardous product recycling with the goal of cost minimization. Hu et al. [33] developed a model of a closed-loop supply chain network for recall with the MINLP model, taking into account uncertainty in demand, uncertainty in the number of recalls and returns, the e-commerce environment, and the time value of money. Chen et al. [34] developed a stochastic mixed-integer programming model of a CLSC network with the goal of minimizing the total cost and the total recall handling response time, based on the urgency of product recalls and the management characteristics of recall emergency management. Pan et al. [35] proposed that recall management is essentially a special type of RL link and developed an improved genetic algorithm-based model for the location and allocation of recall centers based on the characteristics of a food recall network. Pharmaceuticals, as one of the items with the greatest impact on human health, have common features with EVBs in terms of time urgency, and Gao [36] and Huang and Wang [37] established an MINLP model for drug recalls with the goal of achieving the minimum cost and time based on the characteristics of multiple levels, multiparty correlation, contingency, and high costs of a drug recall. RL networks are solved using a heuristic algorithm.

To summarize, from the above studies, it can be seen that the methods used for RL network optimization are mainly based on an MINLP. Single- and multiobjective methods have been constructed; single and multiple periods have been considered. Overall, the existing research is mainly based on multiple objectives and periods for RL networks. In the future, recall RL network design research will pay more attention to being green, environmental protection, and safety.

The above-mentioned studies have the goal of minimizing costs, maximizing the economy, and minimizing time [38] as well as minimizing carbon emissions. However, there has been little research on RL for the recall of EVBs in EVs with the goals of minimizing safety and environmental risks and maximizing social responsibility and economic benefit.

In recent years, EVBs have become a research hotspot, although little research has been conducted on the design of RL networks for recalls with EVBs as the subject of study. The development of a rational recall RL network is critical to the rapid and safe recall of faulty EVBs.

Therefore, considering the urgency of the real-life problem, and there is still a certain gap in the research on EVBs recall. In this paper, we consider the safety and environmental risks, social responsibility, and economic benefits as the goal, comprehensively consider various factors such as an RL recall time, testing costs, packaging costs, site setup scale, transportation costs, operating costs, the number of jobs created, and storage costs, and collect 364 EVB service outlets in Shanghai to build a multiobjective multiperiod MINLP model that considers the recall risk to determine the location and number of each RL facility and the flow and direction of the RL of an EVB recall for each facility.

3. Methodology—Fourier Model

This study will use the Fourier prediction model to forecast the sales volume of new energy vehicles.

According to the definition of the Fourier series [39, 40], the periodic function $f(x)$ can be described by a linear combination of trigonometric functions. If the period of $f(x)$ is T, the angular frequency $\Omega = 2\pi/T$, and the frequency $f = 1/T$. The expression for the Fourier series expansion is

$$f(x) = a_0 + a_1 * \cos(x * \Omega) + b_1 * \sin(x * \Omega) + a_2 * \cos(2x * \Omega) + b_2 * \sin(2x * \Omega). \quad (1)$$

Fourier model prediction is calculated to find the best result under the minimum variance estimate of the prediction error. The geometric description of the best prediction principle based on the Fourier model is shown in Figure 1. In order to minimize the prediction error $e_t(l)$, the best prediction $x_t(l)$ must be the orthogonal projection of the vector x_{t+l} in the three-dimensional space.

The Fourier prediction model will be fitted and predicted using the cftool toolbox inside Matlab 2018a for the relevant data.

4. Recall Reverse Logistics Model

4.1. Problem Definition. The objective of this study is to design an RL network for EVBs that considers the risk of recall. The network setup testing cost indexes consider the safety risk of an EVB recall, and packaging cost indices consider the environmental pollution risk of an EVB recall and establish an RL infrastructure for an EVB recall that includes service outlets, recall sites, recall processing centers, recall transfer centers, and echelon use centers. As shown in Figure 2, EVBs are recalled from the owners at the service outlets for a short period of storage and then transported in batches to the recall processing center. After sorting, picking, testing, and packaging at the recall processing center, the EVBs will be shipped to the recall transfer center and consolidated to the echelon use center. At the recycling center, the recalled EVBs will be sorted into different categories for recycling, parts reuse, material reuse, or resource treatment.

In this study, a multiobjective and multiperiod MINLP model is established based on the characteristics of the EVBs and considers the recall risk to achieve the coordinated development of safety and environmental benefits and economic benefits, providing a reference for the management decisions of relevant personnel.

4.2. Model Assumptions. The assumptions of the proposed model are as follows:

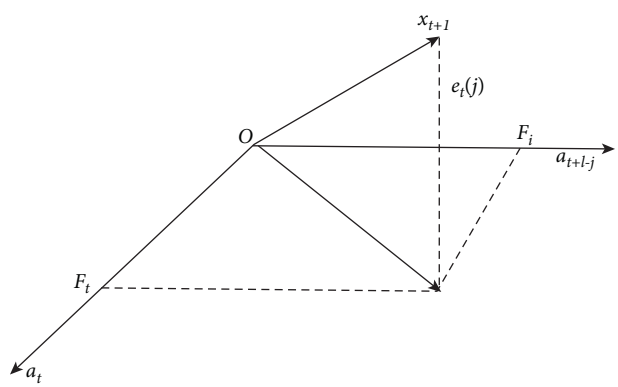

Figure 1: Geometric representation of the best prediction.

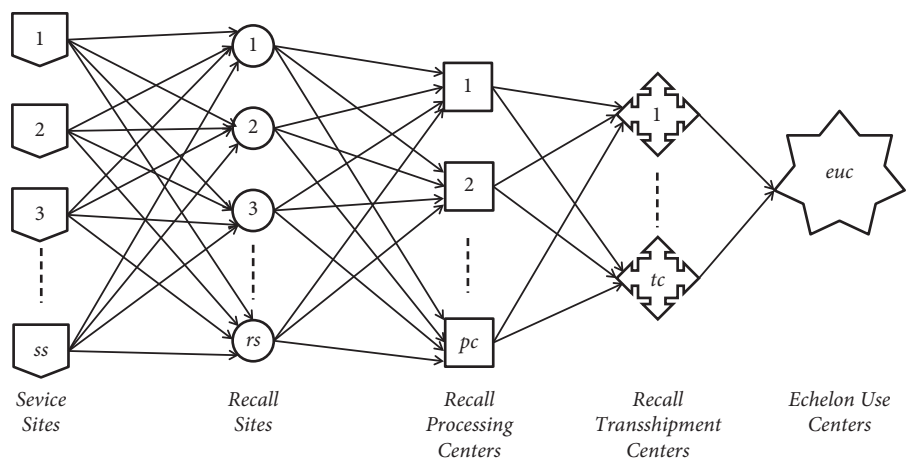

Figure 2: Recall RL network for EVBs.

(1) All EVBs are collected through service outlets to recall sites, and there will be no direct delivery of EVBs to recall sites by vehicle owners or EVB owners.

(2) Recall processing centers, recall transfer centers, and echelon use centers obey an even distribution of storage costs.

(3) The recall sites, recall processing centers, recall transfer centers, and echelon use centers are not engaged in any acts or events that damage the EVBs during storage.

(4) At the end of the operating period, the recall sites send all EVBs to the recall processing center.

(5) To ensure the reliability of the recall network and its stable operation in the case of an emergency, it is assumed that all EVBs of the recalled EVs will need to be collected for test, repair, disposal, echelon use, or resource treatment.

4.3. Model Formulation

4.3.1. Sets. In this section, the collection, model parameters, and decision variable symbols are described, and the proposed multiobjective multiperiod MINLP model is configured using the mentioned components.

R: set of recall sites, index by r

S: set of recall processing centers, index by s

T: set of recall transfer centers, index by t

E: set of echelon use centers, index by e

P: set of Period, index by p

4.3.2. Parameters

fi_s^p: fixed input cost of establishing a recall processing center at the alternative site s in period p

fi_t^p: fixed input cost of establishing a recall transfer center at the alternative site t in period p

fi_e^p: fixed input cost of establishing an echelon use center at the alternative site e in period p

jc_s^p: number of jobs created in the recall processing center s in period p

jc_{tc}^p: number of jobs created in the recall transfer center t in period p

jc_e^p: number of jobs created in the echelon use center e in period p

sc: unit transportation costs per EVB

pkc: unit packaging cost per EVB

dc: unit testing cost per EVB

wc_s: storage cost per unit per day at the recall processing center s

wc_t: storage cost per unit per day at the recall transfer center t

wc_e: storage cost per unit per day at the echelon use center e

oc_s: unit operating costs of the recall processing center s

oc_t: unit operating costs of the recall transfer center t

oc_e: unit operating costs of echelon use center e

lc_s: daily labor cost per employee at the recall processing center s

lc_t: daily labor cost per employee at the recall transfer center t

lc_e: daily labor cost per employee at echelon use center e

dt_{rs}: distance from the recall sites r to the recall processing center s

dt_{st}: distance from the recall processing center s to the recall transfer center t

dt_{te}: distance from the recall transfer center t to the echelon use center e

M_s: maximum processing capacity of the recall processing center s

M_t: maximum processing capacity of the recall transfer center t

M_e: maximum processing capacity of echelon use center e

W_s^p: maximum inventory capacity of recall processing center s

W_t^p: maximum inventory capacity of recall transfer center t

W_e^p: maximum inventory capacity of echelon use center e

L_s: maximum construction of recall processing center s

L_t: maximum construction of recall transfer center t

L_e: maximum construction of echelon use center e

Q_f: predicted number of recalls for EVBs

Pr: value generated after echelon use of EVBs (after costs)

β: utilization rate of echelon use center $e, 0 \le \beta \le 1$

δ_1, δ_2: discount cut-off point for transport size

γ_1, γ_2: penalty cut-off point for transport distance

$f(T_{r0}, dt_{r0}) = sc \cdot \delta\gamma$. Here, δ represents the discount rate, depending on the amount of transport T_{rs}^p between the recall site r and the recall processing center s. In addition, γ represents the penalty rate, depending on the time to recall of the EVB to be recalled to recall site r, where time is replaced by distance, depending on the distance dt_{rs}between the recall site r and the recall processing center s.

$$\delta = \begin{cases} \delta_0, & \text{for } T_{ri} \le k_1, \\ \delta_1, & \text{for } k_1 < T_{ri} \le k_2, \\ \delta_2, & \text{for } T_{ri} > k_2 \end{cases}$$

$$\gamma = \begin{cases} \gamma_0, & \text{for } dt_{ri} \le g_1, \\ \gamma_1, & \text{for } g_1 < dt_{ri} \le g_2, \\ \gamma_2, & \text{for } dt_{ri} > g_2. \end{cases}$$

4.3.3. Variables

$$Y_{rs}^p = \begin{cases} 1, & \text{recall sites } r \text{ assigned to recall processing center } s \text{ in period } p, \\ 0, & \text{otherwise} \end{cases};$$

$$Y_{st}^p = \begin{cases} 1, & \text{recall processing center } s \text{ is assigned to recall transfer center } t \text{ in period } p, \\ 0, & \text{otherwise} \end{cases};$$

$$Y_{te}^p = \begin{cases} 1, & \text{recall transfer center } t \text{ is assigned to echelon use center } e \text{ in period } p, \\ 0, & \text{otherwise} \end{cases};$$

$$Y_s^p = \begin{cases} 1, & \text{recall processing center } s \text{ is established in period } p, \\ 0, & \text{otherwise} \end{cases};$$

$$Y_t^p = \begin{cases} 1, & \text{recall transfer center } t \text{ is established in period } p, \\ 0, & \text{otherwise} \end{cases};$$

$$Y_e^p = \begin{cases} 1, & \text{echelon use center } e \text{ is established in period } p, \\ 0, & \text{otherwise} \end{cases};$$

T_{rs}^p: the number of EVBs transported from the recall sites r to the recall processing center s in period p;

T_{st}^p: the number of EVBs transported from the recall processing center s to the recall transfer center t in period p;

T_{te}^p: the number of EVBs transported from the recall transfer center t to the echelon use center e in period p.

4.4. Objective Functions. In this study, the three objectives are divided into two parts. The first part is the level of safety and environmental responsibility, including subobjective one (SET) and subobjective two (SR). The second part is the level of economic benefit, including subobjective three (EB). In this study, we integrate the safety and environmental responsibilities and economic benefits to maximize the overall benefits. Equation (2) is as follows:

$$\max F = (\text{SR} - \text{SET}) + \text{EB}. \tag{2}$$

Subobjective 1. Minimize safety and environmental risks, minimize response time

$$\text{SET} = \sum_p \sum_s \sum_t dt_{st} \cdot Y_t^p + \sum_p \sum_t \sum_e \frac{Y_e^p}{M_e^p \cdot dt_{te} \cdot \beta} + \sum_p \sum_r \sum_s dt_{rs} \cdot Y_s^p. \tag{3}$$

Subobjective 2. Maximize social responsibility

$$\text{SR} = \sum_p \left(\sum_s jc_s^p \cdot Y_s^p + \sum_{tc} jc_t^p \cdot Y_t^p + \sum_{euc} jc_e^p \cdot Y_e^p \right). \tag{4}$$

Subobjective 3. Maximize economic efficiency

$$\mathrm{EB} = \sum_p \sum_e W_e^p \cdot \mathrm{Pr} \cdot \beta - \mathrm{EC}, \tag{5}$$

$$\mathrm{EC} = C_1 + C_2 + C_3 + C_4 + C_5 + C_6 + C_7, \tag{6}$$

$$C_1 = \sum_p \left(\sum_s fi_s^p \cdot Y_s^p + \sum_t fi_t^p \cdot Y_t^p + \sum_e fi_e^p \cdot Y_e^p \right), \tag{7}$$

$$\begin{aligned} C_2 = &\sum_p \sum_r \sum_s sc \cdot d_{rs} \cdot T_{rs}^p + \sum_p \sum_s \sum_t sc \cdot dt_{st} \cdot T_{st}^p \\ &+ \sum_p \sum_t \sum_e sc \cdot dt_{te} \cdot T_{te}^p, \end{aligned} \tag{8}$$

$$C_3 = \sum_p \sum_r \sum_s dc \cdot T_{rs}^p, \tag{9}$$

$$C_4 = \sum_p \sum_r \sum_s pkc \cdot T_{rs}^p, \tag{10}$$

$$C_5 = \sum_p \left(\sum_s wc_s \cdot W_s^p + \sum_t wc_t \cdot W_t^p + \sum_e wc_e \cdot W_e^p \right), \tag{11}$$

$$C_6 = \sum_p \left(\sum_s jc_s^p \cdot lc_s + \sum_t jc_t^p \cdot lc_t + \sum_e jc_e^p \cdot lc_e \right), \tag{12}$$

$$C_7 = \sum_p \sum_r \sum_s oc_s \cdot T_{rs}^p + \sum_p \sum_s \sum_t oc_t \cdot T_{st}^p + \sum_p \sum_t \sum_e oc_e \cdot T_{te}^p. \tag{13}$$

Equation (2) indicates the optimal value of recall RL network. Equation (3) indicates that the recall of EVBs should ensure the safety of the city and reduce environmental pollution, and EVBs with potential problems should be recalled within the shortest possible time such that the risk of safety and pollution is minimized and the response time is the shortest. Here, $\sum_p \sum_r \sum_s dt_{rs} \cdot Y_s^p$ represents the distance between the recall processing center s and the recall site r, $\sum_p \sum_s \sum_t dt_{st} \cdot Y_t^p$ represents the distance between the recall transfer center t and recall processing center s, and $\sum_p \sum_t \sum_e Y_e^p / W_e^p \cdot dt_{te} \cdot \beta$ represents the size of the echelon use center e and the distance to the recall transfer center t. Equation (4) indicates the maximization of the social responsibility of an enterprise that recalls the traction batteries of EVs, and social responsibility is expressed by the number of jobs created; in addition, $\sum_s jc_s^p \cdot Y_s^p$ represents the number of jobs created in the recall processing center, $\sum_t jc_t^p \cdot Y_t^p$ indicates the number of jobs created in the recall transfer center, and $\sum_e jc_e^p \cdot Y_e^p$ represents the number of jobs created in the echelon use center. Equation (5) indicates the economic benefits of the recall enterprise, and $W_e^p \cdot \mathrm{Pr} \cdot \beta$ represents the economic income of the recall enterprise. Equation (6) indicates the economic cost of the recall enterprise. Equation (7) represents the sum of the construction costs for each period, $\sum_s fi_s^p \cdot Y_s^p$ is the construction cost of the recall processing center, $\sum_t fi_t^p \cdot Y_t^p$ is the construction cost of the recall transfer center, and $\sum_e fi_e^p \cdot Y_e^p$ represents the construction cost of the echelon use center. Equation (8) indicates the sum of transport costs per period, $\sum_p \sum_r \sum_s sc \cdot dt_{rs} \cdot T_{rs}^p$ represents the cost of transportation from the recall site to the recall processing center, $\sum_p \sum_s \sum_t sc \cdot dt_{st} \cdot T_{st}^p$ is the cost of transportation from the recall processing center to the recall transfer center, and $\sum_p \sum_t \sum_e sc \cdot dt_{te} \cdot T_{te}^p$ represents the cost of transportation from the recall transfer center to the echelon use center. Equation (9) is the sum of the testing costs of the recalled EVBs. Equation (10) shows the sum of the packaging costs of the recalled EVBs. Equation (11) indicates the sum of the storage costs for each period, $\sum_s wc_s \cdot W_s^p$ represents the storage costs for the recall processing centers, $\sum_t wc_t \cdot W_t^p$ represents storage costs for the recall transfer centers, and $\sum_e wc_e \cdot W_e^p$ represents the storage costs for echelon use centers. Equation (12) indicates the sum of the labor costs for each period, $\sum_s jc_s^p \cdot lc_s$ represents the labor costs for the recall processing centers, $\sum_t jc_t^p \cdot lc_t$ represents the labor costs for the recall transfer centers, and $\sum_e jc_e^p \cdot lc_e$represents the labor costs for echelon use centers. Equation (13) indicates the operating costs, $\sum_p \sum_s \sum_t oc_s \cdot T_{rs}^p$ is the operating costs for the recall processing centers, $\sum_p \sum_s \sum_t oc_t \cdot T_{st}^p$ represents the operating costs for recall transfer centers, and $\sum_p \sum_t \sum_e oc_e \cdot T_{te}^p$ is the operating costs for echelon use centers.

The above are subject to the following:

$$\sum_s Y_{rs}^p = 1, \quad \forall r, p, \tag{14}$$

$$\sum_t Y_{st}^p = 1, \quad \forall s, p, \tag{15}$$

$$\sum_e Y_{te}^p = 1, \quad \forall t, p, \tag{16}$$

$$\sum_s T_{rs}^p \cdot Y_s^p = Q_f, \quad \forall r, p, \tag{17}$$

$$\sum_s T_{rs}^p \cdot Y_s^p = \sum_t T_{st}^p \cdot Y_t^p, \quad \forall r, p, \tag{18}$$

$$\sum_t T_{st}^p \cdot Y_t^p = \sum_e T_{te}^p \cdot Y_e^p, \quad \forall s, p, \tag{19}$$

$$\sum_s T_{rs}^p \cdot Y_s^p = \sum_t W_s^p \cdot Y_s^p, \quad \forall r, p, \tag{20}$$

$$\sum_t T_{st}^p \cdot Y_t^p = \sum_e W_t^p \cdot Y_t^p, \quad \forall s, p, \tag{21}$$

$$\sum_e T_{te}^p \cdot Y_e^p = \sum_e W_e^p \cdot Y_e^p, \quad \forall t, p, \tag{22}$$

$$\sum_r T_{rs}^p \cdot Y_s^p \le M_s, \quad \forall s, p, \tag{23}$$

$$\sum_s T_{st}^p \cdot Y_t^p \le M_t, \quad \forall t, p, \tag{24}$$

$$\sum_{t} T_{te}^{p} \cdot Y_{e}^{p} \leq M_{e}, \quad \forall e, p, \tag{25}$$

$$W_{s}^{p} \cdot Y_{s}^{p} \leq V_{s}, \quad \forall s, p, \tag{26}$$

$$W_{t}^{p} \cdot Y_{t}^{p} \leq V_{t}, \quad \forall t, p, \tag{27}$$

$$W_{e}^{p} \cdot Y_{e}^{p} \leq V_{e}, \quad \forall e, p, \tag{28}$$

$$1 \leq \sum_{s} Y_{s}^{p} \leq L_{s}, \quad \forall p, \tag{29}$$

$$1 \leq \sum_{t} Y_{t}^{p} \leq L_{t}, \quad \forall p, \tag{30}$$

$$1 \leq \sum_{c} Y_{e}^{p} \leq L_{e}, \quad \forall p, \tag{31}$$

$$T_{rs}^{p}, T_{st}^{p}, T_{te}^{p} \geq 0, \quad \forall r, s, t, e, p, \tag{32}$$

$$W_{s}^{p}, W_{t}^{p}, W_{e}^{p} \geq 0, \quad \forall r, s, t, e, p, \tag{33}$$

$$Y_{rs}^{p}, Y_{s}^{p}, Y_{t}^{p}, Y_{e}^{p} \in \{0, 1\}, \quad \forall r, s, t, e, p. \tag{34}$$

Constraint (14) indicates that, in period p, there is a corresponding processing center s for each recall site r. Constraint (15) indicates that, in period p, each selected recall processing center s has a corresponding recall transfer center t. Constraint (16) shows that, in period p, each selected recall transfer center t has a corresponding echelon use center e. Constraint (17) indicates that, in period p, the number of EVBs transported from the recall sites to the recall processing centers is equal to the number of recalls recovered from the recall sites. Constraint (18) shows that, in period p, the number of EVBs transported from the recall sites to the recall processing centers is equal to the number of EVBs transported from the recall processing centers to the recall transfer centers. Constraint (19) indicates that, in period p, the number of EVBs transported from the recall treatment centers to the recall transfer centers is equal to the number of EVBs transported from the recall transfer centers to the echelon use centers. Constraint (20) shows that, in period p, the number of EVBs transported from the recall sites to the recall processing centers is equal to the number of EVBs in stock at the recall processing centers. Constraint (21) indicates that, in period p, the number of EVBs transported from the recall processing centers to the recall transfer centers is equal to the inventory level of the recall transfer centers. Constraint (22) shows that, in period p, the number of EVBs transported from the recall transfer centers to the echelon use centers is equal to the inventory level of the echelon use centers. Constraint (23) indicates that, in period p, the number of EVBs transported from the recall sites to the recall processing center does not exceed the maximum processing capacity of the recall processing center. Constraint (24) shows that, in period p, the number of EVBs transported from the recall processing centers to the recall transfer center does not exceed the maximum processing capacity of the recall transfer center. Constraint (25) indicates that, in period p, the number of EVBs transported from the recall transfer centers to the echelon use centers does not exceed the maximum processing capacity of the echelon use centers. Constraint (26) shows that, in period p, the number of EVBs at the recall transfer center does not exceed the maximum inventory of the recall processing center. Constraint (27) indicates that, in period p, the number of EVBs in the recall transfer center does not exceed the maximum inventory of the recall transfer center. Constraint (28) shows that, in period p, the number of EVBs in the echelon use center does not exceed the maximum inventory in the echelon use center. Constraint (29) indicates that, in period p, the number of alternatively established recall processing centers does not exceed the maximum set number of recall processing centers. Constraint (30) shows that in period p, the number of alternatively established recall transfer centers does not exceed the maximum set number of recall transfer centers. Constraint (31) indicates that, in period p, the number of alternatively established echelon use centers does not exceed the maximum set number of echelon use centers. Finally, constraints (32) and (33) indicate that the variable is nonnegative, and constraint (34) shows that the guaranteed decision variable is 0 or 1.

Table 1: Sales of EVs in Shanghai.

Year	Sales
2011	12
2012	298
2013	514
2014	11271
2015	47446
2016	45474
2017	61354
2018	73724

5. Computational Results

In this section, a case study of Shanghai EVBs is first described, and the calculation results are then presented.

5.1. Case Study. This study takes the Shanghai EVB recall as an example and establishes an RL network based on the recall volume of EVBs during the next three years. The locations of RL infrastructure such as service outlets, recall sites, recall processing centers, recall transfer centers, and echelon use centers were identified, and the flow directions were determined.

Table 1 shows the sales volume of EVs in Shanghai during the past years, as released by the vehicle management department of the Shanghai public security organs.

Hao et al. [41] forecasted the number of end-of-life vehicles using a hybrid model based on grey model and artificial neural network. This study is based on the actual

sales volume of EVs in Shanghai from 2011 to 2018, as shown in Table 1, the Fourier transformation [39, 40] is used to fit the merger prediction, the functional relationship is shown in Figure 3 and equation (34), and the predicted sales volume of EVs from 2019 to 2021 is shown in Table 2.

$$f(x) = a_0 + a_1 * \cos(x * \Omega) + b_1 * \sin(x * \Omega) + a_2 * \cos(2x * \Omega) + b_2 * \sin(2x * \Omega). \tag{35}$$

The correlation coefficients are as follows:

$$\begin{aligned} a_0 &= 51200, \\ a_1 &= -919.3, \\ a_2 &= -3835, \\ b_1 &= 49070, \\ b_2 &= -11200, \\ w &= 0.4253. \end{aligned} \tag{36}$$

According to the Matlab 2018a test, under a 95% confidence interval, as shown in Table 3, R-square tends toward 1, indicating that the Fourier function has a good fit.

According to equation (35), the sales volume of EVs in Shanghai from 2019 to 2021 is calculated as shown in Table 2.

According to the information released by the Ministry of Industry and Information Technology of China on EVB recycling service outlets, as shown in Table 4, there are 364 service outlets in Shanghai (as of July 20, 2020), and only the Huangpu District in Shanghai has no service outlets as of yet.

The sales volume of EVs in a certain region is correlated with the number of 4S shops in the region Han [42], and for the living standard of urban residents, their consumption-type expenditure will have a significant impact on the number of 4S cars, and the proportion of scrapped EVs in different districts to the total number of scrapped EVs is the same as the number of 4S shops in different districts to the total number of 4S shops. Therefore, this method is also adopted in the present study to obtain the sales volume of EVs in each district of Shanghai, as shown in Table 5.

The number of recalls is highly correlated with market ownership and annual sales volume, particularly the annual sales volume [43]. On the one hand, the recall rate reflects the number of defective vehicles, and on the other hand, it also reflects the importance that manufacturers attach to the quality of the vehicles [44]. The recall rate R_r is the ratio of the annual number of recalled EVs (N_r) to the annual number of EVs (N_s) sold; that is, $R_r = N_r/N_s$. The average annual recall rate of EVs was determined according to Zhang and Shen [44], which shows that the average recall rate of Chinese vehicles during 2004–2017 is 17.53%. Based on this recall rate, the recall of EVs is obtained as shown in Table 6. Wu et al. [45] found that the best service life of an EVB is 5 years. As shown in Table 7, Niu [46] conducted a statistical analysis of Chinese vehicle recalls and found that the new vehicles with the highest number of recalls are those with a service life of less than 1 year, and the recall rate within 3 years is close to 80%.

The recall volume during the first three years reached 77% [46], which covered most of the recall demand. The legal working days are 250 per year, as shown in Table 8, which calculates the recall volume for the next 3 years for each district in Shanghai.

Considering the special characteristics of EVs, the number of EVs recalled is an integer, and there is no fractional number of recalls. The average daily number of recalls is rounded up to solve the average daily value, and thus, there may be cases in which the average daily value multiplied by the annual working day value is greater than the total number of recalls.

Tables 9–11 show the simulated coordinate locations of each facility [15]. Table 9 shows the locations of the alternative recall sites, Table 10 shows the locations of the alternative recall processing centers, and Table 11 shows the locations of the alternative recall transfer centers. Table 12 shows the locations of the alternative echelon use centers. Table 13 shows the assignment of the parameters for each recall processing center, recall transfer center, and echelon use center.

The transport distance between points is assumed to be the Euclidean distance.

The average capacity of an EVB is approximately 500 kWh, the average weight is 500 kg, and the value generated by each ton of EVBs is RMB 3,000 [47], and thus, the value generated by each EVB is RMB 1,500. The assignment of the recall processing center and the recall transfer center construction costs, labor costs, utilization rate of echelon use, value generated by echelon use, and maximum inventory capacity of the recall processing center are from Han [42]. The transportation cost per EVB is 12.3 Yuan/km [28]. Each EVB costs 0.24 Yuan/day for storage at the recall processing center, recall transfer center, and echelon use center [48]. The average packaging cost of an EVB is 232 Yuan [49]; however, when considering that the packaging is a leak-proof and corrosion-proof logistics turnover box and, according to statistics, can be reused as many as 20 times, the average single packaging cost is 11.6 Yuan. Physical inspection and functional battery testing of an EVB take 1 hour [49]. According to the data released by the Shanghai Social Security Bureau in 2019, the hourly minimum wage is 22 Yuan per hour, and thus, the cost of testing the EVB is 22 Yuan. The assignment of the transport size discount/penalty rate and transport distance discount/penalty rate is from Diabat et al. [50].

5.2. Implementation. Kronqvist et al. [51] and Wang et al. [52] presented a theoretical study and empirical analysis of LINGO solving MINLP models. An MINLP model including 822 variables and 247 constraint conditions is constructed. The optimal solution was found using Extended LINGO V18.0/DELL XPS 13. The case study shows that the maximum benefit of the three periods of the RL network for Shanghai's EVB recall is RMB 433,125,300, as shown in Table 14.

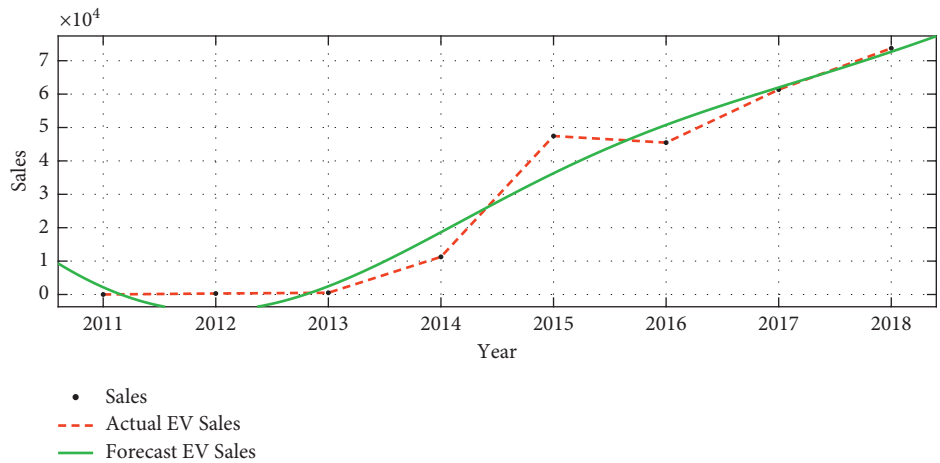

Figure 3: Fourier function prediction chart.

Table 2: EV sales in Shanghai (2019–2021).

Year	Sales
2019	82,221
2020	94,247
2021	101,510

Table 3: Fourier function fit results.

Parameters	Explain
SSE	244,300,000
R-square	0.9621
Adjusted R-square	0.8672
RMSE	11050

Table 4: Quantity of EVB service outlets in each district of Shanghai.

District	Number of service sites	P (%)
Pudong New Area	81	22.25
Minhang District	61	16.76
Baoshang District	44	12.09
Jiading District	29	7.97
Putuo District	29	7.97
Songjiang District	26	7.14
Fengxian District	22	6.04
Qingpu District	18	4.95
Xuhui District	17	4.67
Yangpu District	13	3.57
Jing'an District	10	2.75
Jinshan District	9	2.47
Chongming District	2	0.55
Zhabei District	2	0.55
Hongkou District	1	0.27

The strategies for site selection for the recall reserve logistics network are shown in Table 15. The value equals 1 if a site is selected in period p; otherwise, it equals zero.

Table 16 shows the EVB flow distribution among the recall and recall processing centers. For instance, the number of EVBs moved from recall site *1* to recall processing center F during period 1 (1, F, 1) is 2,240.

Table 17 shows the EVB flow distribution among the recall processing centers and recall transfer centers. For instance, the number of EVBs moved from recall processing center C to recall transfer center J in period *2* (C, J, 2) is 4,156.

Table 18 shows the EVB flow distribution among the recall transfer centers and echelon use centers. For instance, the number of EVBs moved from recall transfer center G to echelon use center K in period *3* (G, K, 3) is 8,176.

5.3. Sensitivity Analysis. This section analyzes the influence of the key parameters on the optimal value of the objective function.

The proposed multiobjective multiperiod MINLP model for the RL network of EVBs, which takes into account the recall risk, is divided into two important parts: the safety and environmental social responsibility level (SR − SET) and the economic benefit level (EB). The safety and environmental responsibility level includes minimizing the risk of social safety and environmental pollution (SET) and maximizing the social responsibility (SR). As the economic benefit (EB), an enterprise can obtain certain profits or control the loss within a certain range under the condition of ensuring safety and environmental protection.

Assuming that the parameter affecting the safety and environmental responsibility (SR − SET) is λ, the parameter affecting the economic benefit (EB)is μ, the parameter affecting the social responsibility (SR) is ϱ, and the parameter affecting the safety and environmental response time (SET) is ϕ. The formula is shown in

$$\max F = \lambda(\varrho \mathrm{SR} - \phi \mathrm{SET}) + \mu \mathrm{EB}. \tag{37}$$

The increase or decrease in these parameters will have a certain impact on the RL network of the EVB recall, and a sensitivity analysis will help enterprise managers make reasonable recall decisions and help relevant government departments formulate reasonable policies.

Table 5: Historic sales of EVs in Shanghai.

Year	2011	2012	2013	2014	2015	2016	2017	2018	2019E	2020E	2021E
Pudong New Area	3	66	114	2,508	10,557	10,118	13,651	16,404	18,294	20,970	22,586
Minhang District	2	50	86	1,889	7,952	7,621	10,283	12,356	13,780	15,796	17,013
Baoshang District	1	36	62	1,363	5,736	5,498	7,418	8,913	9,941	11,394	12,273
Jiading District	1	24	41	898	3,781	3,624	4,890	5,876	6,553	7,511	8,090
Putuo District	1	24	41	898	3,781	3,624	4,890	5,876	6,553	7,511	8,090
Songjiang District	1	21	37	805	3,388	3,247	4,381	5,264	5,871	6,729	7,248
Fengxian District	1	18	31	681	2,866	2,747	3,706	4,453	4,966	5,693	6,131
Qingpu District	1	15	25	558	2,349	2,251	3,037	3,649	4,070	4,665	5,025
Xuhui District	1	14	24	526	2,216	2,124	2,865	3,443	3,840	4,401	4,741
Yangpu District	0	11	18	402	1,694	1,623	2,190	2,632	2,935	3,365	3,624
Jing'an District	0	8	14	310	1,305	1,251	1,687	2,027	2,261	2,592	2,792
Jinshan District	0	7	13	278	1,172	1,123	1,515	1,821	2,031	2,328	2,507
Chongming District	0	2	3	62	261	250	337	405	452	518	558
Zhabei District	0	2	3	62	261	250	337	405	452	518	558
Hongkou District	0	1	1	30	128	123	166	199	222	254	274
Total sales volume	12	298	514	11,271	47,446	45,474	61,354	73,724	82,221	94,247	101,510

Table 6: Number of EVs recalled in Shanghai.

Year	2017	2018	2019	2020	2021
Pudong New Area	2,393	2,876	3,207	3,676	3,959
Minhang District	1,803	2,166	2,416	2,769	2,982
Baoshang District	1,300	1,562	1,743	1,997	2,151
Jiading District	857	1,030	1,149	1,317	1,418
Putuo District	857	1,030	1,149	1,317	1,418
Songjiang District	768	923	1,029	1,180	1,271
Fengxian District	650	781	871	998	1,075
Qingpu District	532	640	713	818	881
Xuhui District	502	604	673	772	831
Yangpu District	384	461	515	590	635
Jing'an District	296	355	396	454	489
Jinshan District	266	319	356	408	440
Chongming District	59	71	79	91	98
Zhabei District	59	71	79	91	98
Hongkou District	29	35	39	45	48
Total number of recalls	10,755	12,924	14,413	16,521	17,795

Table 7: Age statistics of recalled cars.

Time interval from production start to recall announcement	Number of recalls	P (%)
Up to 1 year	108	34
2 years	80	25
2-3 years	59	18
3–10 years	68	21
More than 10 years	5	2

Here, we conducted a sensitivity experiment to expand or shrink each parameter to test the effect of parameter changes on the overall target. For each parameter, there are three different rates of change, that is, 0.5, 1, and 1.5 [52], as shown in the third column of Tables 19 and 20. The corresponding parameter changes for each parameter in the experimental group were 0.5, 1, and 1.5, and the remaining four parameters were set to 1.

Thus, there are $3 \times 2 = 6$ experimental instances in Table 19 and $3 \times 2 = 6$ experimental instances in Table 20.

From Table 18 and Figure 4, it can be seen that the safety and environmental social responsibility parameters λ have a small impact on the objective function results, and the economic efficiency parameter μ has a large impact. It can be seen that parameter λ does not have a significant impact on the performance of the recall RL

Table 8: Predicted volume of EV recalls in Shanghai over the next 3 years.

Year	2020		2021		2022	
	Total	Daily average	Total	Daily average	Total	Daily average
Pudong New Area	2,240	9	2,569	11	2,842	12
Minhang District	1,687	7	1,935	8	2,141	9
Baoshang District	1,217	5	1,396	6	1,544	7
Jiading District	802	4	920	4	1,018	5
Putuo District	802	4	920	4	1,018	5
Songjiang District	719	3	824	4	912	4
Fengxian District	608	3	697	3	772	4
Qingpu District	498	2	572	3	632	3
Xuhui District	470	2	539	3	597	3
Yangpu District	359	2	412	2	456	2
Jing'an District	277	2	318	2	351	2
Jinshan District	249	1	285	2	316	2
Chongming District	55	1	64	1	70	1
Zhabei District	55	1	64	1	70	1
Hongkou District	27	1	31	1	34	1
Total number of recalls	10,067	47	11,547	55	12,775	61

Table 9: Coordinate locations of the recall sites.

No.	X	Y
1	15.69	3.80
2	18.67	24.28
3	1.60	59.13
4	9.43	2.27
5	49.08	54.43
6	33.14	10.85
7	28.62	50.00
8	24.86	59.39
9	3.42	35.85
10	33.23	21.90
11	45.32	27.23
12	46.37	6.36
13	24.93	32.60
14	28.07	33.38
15	2.77	0.5

Table 10: Alternative recall processing centers.

No.	X	Y	Code
1	43.97	49.89	A
2	1.57	12.65	B
3	41.23	30.25	C
4	5.04	58.97	D
5	24.79	19.00	E
6	16.18	20.66	F

network, but parameter μ has a significant impact on the performance of the recall RL network. This obvious interest gap makes some companies in the development of recall decisions or the design of a recall RL network tend to earn maximum profit while ignoring safety issues and environmental pollution.

Parameter λ is jointly influenced by ϱ and ϕ. Therefore, parameters ϱ and ϕ are analyzed separately. From Figure 5, we can see that, based on the effect of the changes in parameter ϱ and parameter ϕ on the function,

Table 11: Alternative recall transfer centers.

No.	X	Y	Code
1	8.58	30.25	G
2	32.36	28.59	H
3	9.58	6.51	I
4	47.54	19.31	J

Table 12: Alternative echelon use centers.

No.	X	Y	Code
1	52.47	64.32	K
2	77.56	78.71	L

parameter ϱ plays a positive correlated role, and parameter ϕ plays a negatively correlated role. The greater the social responsibility, the more obvious the increase in the target function; in addition, the higher the requirements for safety and environmental protection as well as the recall response time, the more obvious the decrease in the target function.

The recall of EVBs is unique owing to its characteristics, such as the existence of certain safety risks, potential environmental pollution, and significant economic benefits. Therefore, while countries are encouraging the recycling or recall of EVBs, they have also issued relevant laws, regulations, or standards, and developed a rigorous and safe recall process. Although there is huge interest in EVBs, we cannot neglect safety and environmental protection and strive for unrestricted profits. This is due to the irreplaceable nature of safety and environmental protection and the weak economics of recalls, requiring policymakers and business managers to rely on standard operations and scientific management to gain appropriate benefits and implement an extended producer responsibility system to actively assume their social responsibility

Table 13: Parameter assignments.

Content	Parameter	Value	Unit of measurement
Construction cost of recall processing center	fi_s^p	10,000,000	Yuan
Construction cost of recall transfer center	fi_t^p	8,000,000	Yuan
Construction cost of echelon use center	fi_e^p	12,000,000	Yuan
Jobs created in a recall processing center	jc_s^p	30	No. of people
Jobs created in a recall transfer center	jc_t^p	45	No. of people
Jobs created in an echelon use center	jc_e^p	100	No. of people
Transportation costs per EVB	sc	12.3	Yuan
Packaging cost per EVB	pkc	11.6	Yuan
Testing cost per EVB	dc	22	Yuan
Daily labor cost per employee	lc	200	Yuan
Storage cost per unit per day at recall processing center	wc_s	0.24	Yuan
Storage cost per unit per day at recall transfer center	wc_t	0.24	Yuan
Storage cost per unit per day at echelon use center	wc_e	0.24	Yuan
Maximum processing capacity of recall processing center	M_s	800	No. of items
Maximum processing capacity of recall transfer center	M_t	800	No. of items
Maximum processing capacity of echelon use center	M_e	1,500	No. of items
Maximum inventory capacity of recall processing center	W_s	800	No. of items
Maximum inventory capacity of recall transfer center	W_t	800	No. of items
Maximum inventory capacity of echelon use center	W_e	2,000	No. of items
	δ_0	1	—
	δ_1	0.8	—
Transport size discount rate	δ_2	0.6	—
	k_1	200	No. of items
	k_2	400	No. of items
	γ_0	1	—
	γ_1	1.1	—
Transport distance penalty rate	γ_2	1.2	—
	g_1	25	km
	g_2	60	km
Value of EVBs after echelon use	Pr	1,500	Yuan/each
Ratio of echelon use	β	0.9	Percentage (%)

Table 14: Solutions.

Optional solution found	Profit (Yuan)
Objective value	433,125,300
Objective bound	433,125,300
Extended solver steps	31
Total solver iterations	14,039
Elapsed runtime seconds	11.07
Model class	MINLP
Solver type	Global

Table 15: Site selection scheme.

Period	RL facilities											
$p = 1$	A	B	C	D	E	F	G	H	I	J	K	L
	0	0	1	1	0	1	1	0	0	1	1	0
$p = 2$	A	B	C	D	E	F	G	H	I	J	K	L
	0	0	1	1	0	1	1	0	0	1	1	0
$p = 3$	A	B	C	D	E	F	G	H	I	J	K	L
	0	0	1	1	0	1	1	0	0	1	1	0

Table 16: Traffic distribution from recall site to recall processing center.

Traffic	Value	Traffic	Value	Traffic	Value
(1, F, 1)	2,240	(1, F, 2)	2,569	(1, F, 3)	2,842
(2, F, 1)	1,687	(2, F, 2)	1,935	(2, F, 3)	2,141
(3, D, 1)	1,217	(3, D, 2)	1,396	(3, D, 3)	1,544
(4, F, 1)	802	(4, F, 2)	920	(4, F, 3)	1,018
(5, C, 1)	802	(5, C, 2)	920	(5, C, 3)	1,018
(6, C, 1)	719	(6, C, 2)	824	(6, C, 3)	912
(7, C, 1)	608	(7, C, 2)	697	(7, C, 3)	772
(8, C, 1)	498	(8, C, 2)	572	(8, C, 3)	632
(9, F, 1)	470	(9, F, 2)	539	(9, F, 3)	597
(10, C, 1)	359	(10, C, 2)	412	(10, C, 3)	456
(11, C, 1)	277	(11, C, 2)	318	(11, C, 3)	351
(12, C, 1)	249	(12, C, 2)	285	(12, C, 3)	316
(13, C, 1)	55	(13, C, 2)	64	(13, C, 3)	70
(14, C, 1)	55	(14, C, 2)	64	(14, C, 3)	70
(15, F, 1)	27	(15, F, 2)	3	(15, F, 3)	34

under the premise of safety and environmental protection. In the development of recall-related policies or standards, we cannot rely on the economic benefits of a single indicator and need to fully consider the social safety and environmental aspects of the community as well as other factors to ensure that an EVB recall can be safe, fast, and green and achieve reusability.

Table 17: Traffic distribution from recall processing center to recall transfer center.

Traffic	Value	Traffic	Value	Traffic	Value
(C, J, 1)	3,622	(C, J, 2)	4,156	(C, J, 3)	4,597
(D, G, 1)	1,217	(D, G, 2)	1,396	(D, G, 3)	1,544
(F, G, 1)	5,226	(F, G, 2)	5,966	(F, G, 3)	6,632

Table 18: Traffic distribution from recall transfer center to echelon use center.

Traffic	Value	Traffic	Value	Traffic	Value
(G, K, 1)	6,443	(G, K, 2)	7,362	(G, K, 3)	8,176
(J, K, 1)	3,622	(J, K, 2)	4,156	(J, K, 3)	4,597

Table 19: Values of parameters λ and μ under different rates of change.

Parameters	Instance no.	Change rate	λ	μ	Value
	1	0.5	**0.5**	1	433,128,000
λ, SR – SET	2	1	**1**	1	433,126,300
	3	1.5	**1.5**	1	433,124,600
	4	0.5	1	**0.5**	216,561,500
μ, EB	5	1	1	**1**	433,126,300
	6	1.5	1	**1.5**	649,691,200

Table 20: The values of parameters ϱ and ϕ under different change rates.

Parameters	Instance no.	Change rate	ϱ	ϕ	μ	Value
	1	0.5	**0.5**	1	1	433,124,800
ϱ SR	2	1	**1**	1	1	433,125,300
	3	1.5	**1.5**	1	1	433,125,700
	4	0.5	1	**0.5**	1	433,127,900
ϕ, SET	5	1	1	**1**	1	433,125,300
	6	1.5	1	**1.5**	1	433,122,600

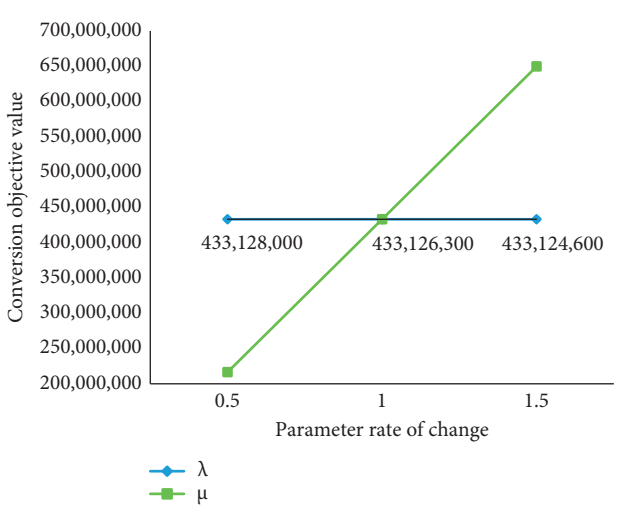

Figure 4: The influence of the change in parameters λ and μ on the optimal value of the objective function.

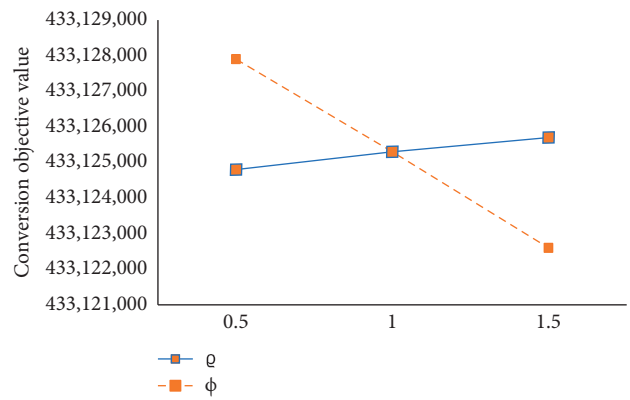

Figure 5: Influence of the change in parameters ϱ and ϕ on the optimal value of the objective function.

6. Conclusion and Future Research

This study aims to solve the problem of optimizing the configuration of RL network facilities for an EVB recall, which is not only a key issue of EVB safety risk management but also an inevitable requirement in promoting the construction of an ecological and green society. First, a multiobjective and multiperiod dynamic model is established to minimize safety and environmental risks, maximize social responsibility and economic benefits, and achieve an RL infrastructure of an EVB recall, including the service outlet, recall site, recall processing center, recall transfer center, and echelon use center. Second, this study focused on the recall of EVBs from Shanghai. Based on historical data and a Fourier fitting, the number of recalled EVBs is predicted for the next 3 years. In this study, based on the locations of these potential RL facilities and the distribution of RL flows in Shanghai's EVB recall, an RL network for each period was considered. Finally, the impact of the weighting of the three factors of safety and environmental protection, social responsibility, and economic benefits on the location decision of a recall RL network was investigated.

The research results are summarized as follows: (1) A multiobjective and multiperiod dynamic site selection model was constructed by combining prediction and MINLP optimization methods, which were used to determine the site selection of each facility and the distribution of the EVB RL network. (2) An EVB recall RL model with considerations regarding safety and the environment was developed, and the synergistic development of safety and environmental protection, social responsibility, and economic benefits was achieved. (3) A sensitivity analysis of the parameters used in the recall RL network was conducted to test the proposed factors that affect the network performance. Although the degree of influence of economic benefit in an objective function is much larger than the degree of influence of safety, environmental protection, and social responsibility, without safety, all economic benefits are zero, and without environmental protection, the economic benefits are greatly discounted.

A study on the design of an RL network for EVBs considering the risk of a recall has helped focus attention on

the management of RL of EVBs. This study uses a combination of predictive techniques and MINLP modeling and considers safety, environmental protection, social responsibility, and economic benefits, which may improve the planning, operation, and management of the RL network for EVB recalls. Furthermore, this study provides possible solutions to maintain the balance between safety, environmental protection, social responsibility, and economic efficiency and also provides a reference for decision-makers to prioritize different factors in different recall situations. This study provides some insight into how to scientifically and effectively design an RL network for the recall of products with certain safety risks or environmental pollution hazards, such as EVBs.

However, owing to the complexity of the RL network and consumer uncertainty, future research still needs to be conducted to improve and supplement this field. In this study, the details between different recalled batteries have not been fully considered, such as the time and cost from vehicle owners to service outlets, the uncertainty in vehicle running time Zhen [53] and EVBs recall time, and the cost of purchasing testing equipment. Therefore, future research will consider the details and quantify the study. Although there are still some shortcomings in this study, it was demonstrated that when there are significant potential benefits and risks, managers should give priority to safety and environmental protection and establish relevant mandatory or guiding systems or standards to properly restrain the behavior of different enterprises. However, policymakers should also provide certain incentives (tax breaks, etc.) to encourage companies to consider safety and environmental protection and to encourage companies and industries to make technological improvements or industrial upgrades. This is of positive significance for building a safe, green, and sustainable ecological society.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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