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An Optimization Model for Reverse Logistics of Electric Vehicle Batteries

Vinh-Thanh Phan[1,2], Thuy-Nhi Le Nguyen [1,2], Ivan Kristianto Singgih[3]

[1] Department of Industrial Systems Engineering, Ho Chi Minh City University of Technology (HCMUT), Ho Chi Minh City, Vietnam

[2] Vietnam National University Ho Chi Minh City, Linh Trung Ward, Ho Chi Minh City, Vietnam

[3] Department of Industrial Engineering, University of Surabaya (UBAYA), Indonesia

Abstract

Currently, the trend toward sustainable development is a top priority in the economic and social agendas of countries worldwide. This global commitment is clearly reflected in the rapid adoption and expansion of electric vehicles, which are widely regarded as a key solution to reducing greenhouse gas emissions and minimizing dependence on fossil fuels. However, the accelerated deployment of EVs has also led to new challenges, particularly the scarcity of critical metals such as lithium, nickel, and cobalt essential elements in the production of lithium-ion batteries. It points out the need for efficient and sustainable systems for battery recovery, recycling, and reuse. This study addresses this challenge by proposing an optimization model for the design and operation of a reverse logistics system dedicated to electric vehicle battery repair, recovery, and recycling. The model integrates three fundamental decision-making dimensions: firstly, the optimal location of battery repair centers; secondly, the selection and placement of recovery and recycling facilities; and the final one is the determination of inventory levels and transportation quantities between all nodes in the system. The model is formulated as a Mixed-Integer Linear Programming (MILP) problem and is optimally solved using CPLEX and Excel. In addition to minimizing total costs including transportation, inventory, and facility opening costs the model explicitly incorporates environmental objectives by reducing carbon emissions from logistics activities and processing technologies. Moreover, although the model is developed for electric vehicle batteries, it can be generalized to other types of electronic waste to support broader circular economy initiatives. The results offer practical implications for supply chain managers, policymakers, and sustainability advocates in designing greener and more resilient reverse logistics networks.

Keywords: reverse logistics, battery recycling, repair center location, carbon emission.

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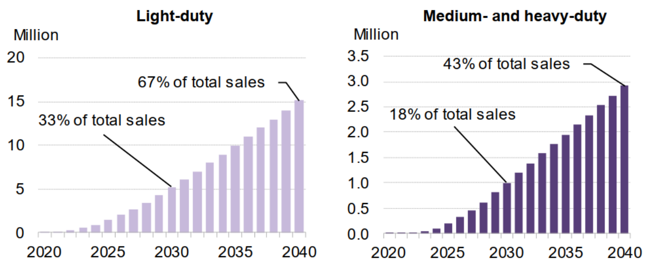
* Corresponding author: thanh.phanvinh7@hcmut.edu.vn

1. Introduction

Nowadays, sustainable development has become an inevitable global trend. Countries and major corporations are accelerating the transition to renewable energy sources and reducing dependence on fossil fuels. Renewable electricity from sources such as wind and solar power is gradually replacing traditional energy. One of the most significant applications of renewable electricity is in electric vehicles (EVs), which help reduce carbon emissions and protect the environment. However, this shift has led to an urgent demand for battery usage, a critical component in EVs and other electronic devices. Batteries have a limited lifespan, and over time, they become a major source of electronic waste if not properly managed.

The rapid global growth of electric vehicles (EVs) has created a pressing need for efficient systems to repair, recover, and recycle lithium-ion batteries to minimize environmental impact and optimize resource usage.

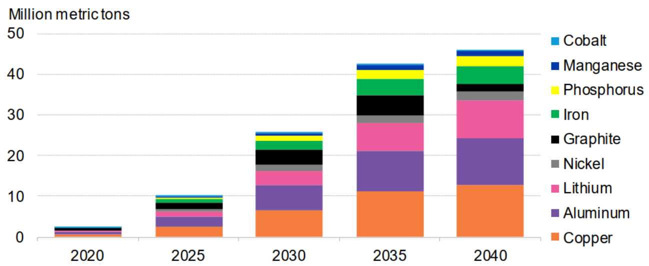
According to BloombergNEF [1] electric vehicles accounted for approximately 17.8% of total global vehicle sales in 2023 and are projected to reach 43% for medium and heavy vehicles, and 67% for light vehicles by 2040, as illustrated (see Fig. 1).



Source: BloombergNEF, government agencies, China Automotive Technology and Research Center, EV-Volumes, Japan Automobile Dealers Association (JADA).

Figure 1. Electric and fuel cell commercial vehicle sales

In parallel, the rapid growth of electric vehicles has also driven up the demand for metals used to produce lithium-ion batteries for energy storage (see Fig. 2).



Source: BloombergNEF

Figure 2. Annual metals demand from lithium-ion batteries under the Net Zero Scenario.

Along with the growing usage of electric vehicles, the requirement for metals used in the production of lithium-ion batteries for energy storage has also increased significantly. Under the Net Zero Scenario, the total quantity of metal for creating lithium-ion batteries is projected to increase nearly tenfold over the next 20 years from less than 5 million metric tons in 2020 to approximately 45 - 47 million metric tons by 2040. Among these, metals such as copper, aluminum, and lithium consistently account for the largest proportion, performed by the orange, purple, and pink segments in the chart. Additionally, graphite (dark gray), which plays a critical role in the anode structure, also contributes a considerable portion. However, this trend poses major challenges for resource extraction and environmental protection, as rising pressure on global mineral supply chains necessitates the development of sustainable mining strategies and the enhancement of material recycling in the future.

In response, researchers have explored ways to reuse and recycle spent batteries. Automotive companies like Tesla, Toyota, and Volkswagen are trying to improve resource efficiency as well as reduce environmental effects by making heavy investments in battery recycling technologies. Another example, Li-Cycle, a North American battery recycling company, is developing technologies capable of recovering over 95% of valuable metals from used batteries, significantly decreasing hazardous waste [1]. Additionally, the European Union has published strict regulations on battery recovery to ensure a sustainable circular economy. Therefore, the need for battery repair, recovery, and recycling is becoming more and more important.

This underscores that developing an optimized logistics system for battery recovery and recycling is not merely an economic solution, but an urgent necessity to ensure sustainable development and safeguard the planet's future. According to BloombergNEF, by 2040, the total demand for metals used in lithium-ion battery production could reach 45-47 million metric tons annually nearly a tenfold increase compared to 2020. At the same time, the rapid growth of electric vehicles - with an estimated 83 million electric cars, trucks, and buses, along with over 340 million electric two and three wheelers expected to be on the road next year is generating an evergrowing volume of spent batteries that must be properly handled.

Without an effective logistics system for collecting, sorting, transporting, and processing end-of-life batteries, the world will face serious consequences: environmental pollution, the loss of valuable resources such as lithium, nickel, and cobalt, and mounting pressure on global supply chains. Therefore, establishing a robust and efficient logistics network is not only essential for cost reduction and economic efficiency, but also plays a critical role in realizing a circular economy, reducing greenhouse gas emissions, and protecting the global ecosystem in the long term.

The study focuses on developing an optimization model for the reverse logistics system of electric vehicle batteries toward sustainable development. By integrating key decisions such as facility location, transportation flow allocation, and technology planning within the MILP framework, the research simultaneously considers both economic and environmental factors. The main contribution of the study is the development of a comprehensive model that optimizes the collection and recycling of end-of-life batteries, thereby reducing emissions, conserving resources, and promoting the establishment of a circular economy in the electric vehicle industry.

2. Literature Review

Recent studies have shown that there is a clear shift from traditional logistics models to reverse logistics systems that focus on sustainability. The three core pillars of economics, environment, and society are increasingly seen as inseparable in the design of modern logistics networks. Dutta *et al.* in 2020 [2] proposed a multi-objective optimization model for end-of-life vehicle recycling that integrates cost-effectiveness, emission reduction, and job creation for local communities. Their study used a mixed integer linear programming approach to determine the optimal configuration of the logistics network to ensure overall efficiency for both the enterprise and the environment.

In addition, Budak, A. in 2020 [3] developed a reverse logistics model for waste electrical and electronic equipment (WEEE) that was also based on the triple bottom line model to balance economic benefits, environmental impact, and social responsi-bility. More recently, Alibakhshi *et al.* in 2024 [4] extended this approach by applying a green reverse logistics model to hospital construction projects (an area with high uncertainty) while taking into account sustainable development goals. These studies not only highlight the key role of reverse logistics in the circular economy but also the need to integrate these three essential dimensions into modern optimization models.

Green logistics and circular economy research suggest that recycling and reusing strategies can help to mitigate environmental impacts and improve efficiency, as demonstrated in the study of Geisendorf & Pietrulla in 2018 [5]. Furthermore, the closed-loop supply chain model development, as an important part to mitigate disruption risks and enhance resource efficiency, is highlighted in the study of Ren-tizelas *et al*. in 2022 [6]. This is particularly relevant to battery products, where stricter regulations on waste treatment and material recovery are being enforced.

The reverse logistics system includes five stages collection, transportation, inspection, processing, and redistribution to return products from customers for repair, replacement, recycling, or disposal. Used or defective items are collected, transported to facilities for evaluation, and then sorted for reuse, recycling, or disposal. In the processing stage, products are repaired, remanufactured, or recovered to ensure that valuable resources are reintegrated into the supply chain as mentioned by Agrawal *et al.* in 2015 [7].

Currently, technologies for battery repair and recycling include high-temperature processing for metal separation from batteries, as studied by Ni *et al.* in 2023 [8], and chemical leaching for metal extraction, investigated by Yao *et al.* in 2018 [9]. Both methods have various advantages and disadvantages in terms of efficiency, cost, and environmental impact. This study classifies these technologies into three levels low, medium, and high based on three criteria: performance, cost, and environmental effects. While the low-level technologies feature lower efficiency, reduced cost, and higher environmental impact, the high-level technologies exhibit greater efficiency, higher cost, and minimal environmental impact.

However, key challenges like high costs, process optimization, and coordination hinder effective implementation. Future research will focus on optimizing reverse logistics, with recycled materials offering a cost-effective alternative amid rising raw material prices.

Battery repair, recovery, and recycling logistics systems not only reduce material costs but also mitigate environmental impacts by minimizing electronic waste and emissions. Studies have shown that the recovery of used products not only allows businesses to capitalize on the remaining value through reuse, remanufacturing, and material recycling, but also contributes to reducing environmental waste and lowering input material costs by Roghanian and Pazhoheshfar in 2014 [10].

This study is built based on previous work related to Location-Routing Problems (LRP) and Inventory Routing Problems (IRP). LRP focuses on determining optimal facility locations within the supply chain considering vehicle routing problems, as investigated by Bramel & Simchi-Levi in 1995 [11]. In contrast, IRP makes an integration of inventory management and transportation decisions to optimize costs and supply chain performance, as seen in the work of Malladi & Sowlati in 2018 [12]. Common solution approaches include linear programming, multi-objective optimization, and heuristic or metaheuristic algorithms, such as those employed by Liu *et al.* in 2022 [13].

Based on previous studies in Table 1, it can be observed that optimization models for the reverse supply chain of electric vehicle batteries mainly focus on key decisions such as facility location selection, transportation flow allocation, technology choice, and capacity planning. Representative studies demonstrate diverse methodological approaches: Wang *et al.* [14] employed a MILP model to integrate collection and recycling decisions, thereby optimizing costs while reducing emissions; Hoyer *et al.* [15], also within the MILP framework, emphasized technology selection and capacity planning, highlighting the critical role of policy and economic feasibility in contexts where input material value is low; Tadaros *et al.* [16] applied MILP to design the reverse logistics network under uncertainty, in which transportation and facility location decisions aim to balance cost and environmental performance; meanwhile, Nguyen-Tien *et al.* [17] developed the MGEE model (Material flow analysis geospatial supply chain model economic and environmental assessment), combining material flow analysis, geospatial supply chain configuration, and economic environmental assessment, clearly illustrating the trade-off between cost and emissions impact across centralized and decentralized scenarios. Overall, the application of both MILP and MGEE in these studies not only demonstrates the capability to address large-scale, multi-constrained problems but also confirms the trend of integrating economic, environmental, and social dimensions (through policy, transportation safety, and resource security) toward sustainable optimization of the electric vehicle battery supply chain.

Compared to previous studies, this paper demonstrates a more comprehensive scope by considering all end-of-life stages (collection, repair, and recycling), while integrating four key decision areas: facility location, transportation flow allocation, technology and capacity planning within the MILP framework. In addition, the study simultaneously evaluates both economic and environmental impact factors, resulting in a total of 9 out of 9 indicators, the highest among the reviewed works.

Table 1. Number of indicators

Paper	End-of-Life Stage			Modeling approach	Decision				Impact factors		Environment
	Collection	Repair	Recycling		Facility location	Inventory	Transportation	Technology	Economic	Environment	
Lei Wang *et al.* (2020)	✓		✓	MILP	✓		✓	✓	✓	✓	**7/9**
Hoyer *et al.* (2015)	✓		✓	MILP				✓	✓		**4/9**
Tadaros *et al.* (2020)	✓		✓	MILP	✓		✓		✓		**5/9**
Nguyen-Tien et al. (2022)	✓		✓	MGEE	✓		✓		✓	✓	**6/9**
This paper	✓	✓	✓	**MILP**	✓	✓	✓	✓	✓	✓	**9/9**

The optimization model plays a crucial role in designing the battery recovery logistics system, as it allows determining which facilities should be opened, where they should be located, and how many are needed to meet recovery demand while minimizing operating costs. By applying linear programming, decisions regarding the quantity of materials to be transported and the optimal transportation routes from sources to receiving facilities are formulated, thereby reducing total transportation costs and limiting CO_2 emissions. At the same time, the model supports inventory balancing at each facility to minimize storage costs and ensure safety. With its flexibility, linear programming can be used to construct various scenarios to adapt to uncertainties in supply and recycling demand. More importantly, decisions are made based on data and quantitative analysis, providing transparency and strong justification for stakeholders.

The Inventory-Location Problem (ILP) is a critical aspect of logistics system management, combining facility location decisions with inventory strategies to optimize system performance. ILP helps balance transportation costs, warehouse operational efficiency, customer service levels, while also considering sustainability aspects such as emission reductions. This study focuses on three main ILP aspects: determining the locations of battery repair centers, and the locations of collection and recycling centers; operational efficiency in managing goods flow between centers and inventories of damaged and reused components; and sustainability factors, including emissions and environmental impacts.

3. Problem statement

The objective of the reverse logistics system is to repair defective products, recover and recycle component in order to optimize costs and reduce CO_2 emissions. This system consists of customers, repair centers, recovery and recycling centers, manufacturing plants, and waste treatment units.

The reverse logistics system begins when the electric vehicle battery becomes faulty and is brought to vehicle maintenance stations, which act as clients of the reverse logistics system. At this point, a preliminary decision is made to either repair, recycle, or discard the battery. If the battery can still be used after repair, it is sent to the repair centers, where inspection and replacement of damaged components are conducted before returning the product to the customer. In cases where the product is no longer functional but is still recyclable, it is sent to recovery and recycling centers for classification, dismantling, and recycling. Valuable and successfully recycled components are then transferred to manufacturing plants for reuse in the production process, contributing to the circular economy model. Finally, if the product cannot be recycled and has no remaining value, it is sent to waste treatment units for safe disposal in accordance with environmental regulations.

The recycled components are then returned to manufacturing plants which contribute to produce new products and play a necessary role in the circular economy model. However, challenges in the recovery process such as determining optimal locations for repair, recovery, and recycling centers, and deciding the transport volumes between centers currently lack specific solutions, thereby reducing system efficiency. This highlights the need to design an optimization solution to improve the operational performance of reverse logistics as well as enhance system sustainability. Fig. 3 and Fig. 4 provide an overview of the mathematical model structure for the battery repair, recovery and recycling logistics system.

The mathematical model structure of the system includes a set of repair centers $r = 1,..., R;$ a set of recovery and recycling centers $u = 1,2,..., U;$ battery supply sources from customers $i = 1,2,..., I$; and the demand from manufacturing plants $m = 1,2,..., M.$

Similar to most reverse logistics system design problems, the system will determine the opening locations of repair centers, recovery, and recycling centers, as well as decide on the quantity of goods to be transported and stored at each center. Sustainability is a key concern in the system and the amount of waste generated from recovery and recycling activities is included in the total system cost. In addition, emissions produced from operations and from the transportation of goods between facilities are also considered, with the objective of minimizing environmental impact. Related costs such as opening costs, transportation costs, inventory holding costs, along with decision variables and dependent variables, are presented in Table 2.

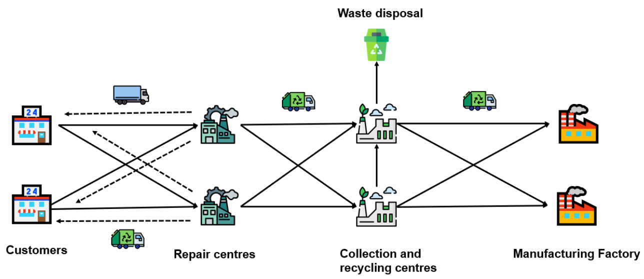


Figure 3. Structure of the battery repair, recovery, and recycling logistics system.

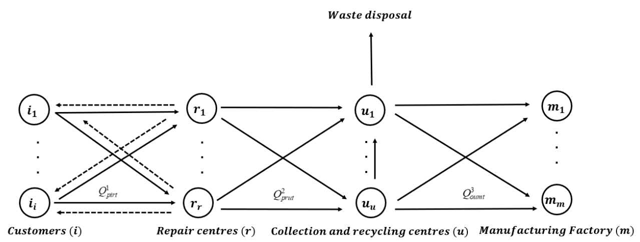


Figure 4. Mathematical model structure of the battery repair, recovery, and recycling logistics system.

4. Model development

4.1. Assumptions

(1) The storage capacity at repair, recovery, and recycling centers is assumed to be unlimited.
(2) Repair centers and recovery and recycling centers incur fixed opening costs for each time period.
(3) Repair and recycling centers are assumed to be opened at the beginning of period 0.
(4) The technology at the repair centers and the recovery and recycling centers is categorized by technological levels (low, medium, high).
(5) Damaged batteries that are successfully repaired will be returned to customers during the same period in which the repair takes place. Batteries that cannot be repaired will be stored at the repair centers and then transferred to the recovery and recycling centers. An environmental cost is incurred for each unit of waste recycled at the recovery and recycling centers. Not all batteries can be repaired; a portion will be recycled or disposed of, and the associated costs are taken into account. Due to environmental objectives, recycled products are prioritized for use, and therefore, the demand from manufacturing plants is considered unlimited.

4.2. Mathematical model

Table 2. Notation

Indices	
I	Set of customers $\left(i = 1,2,...,I\right)$
R	Set of repair center $\left(r = 1,2,...,R\right)$
U	Set of collection and recycling center $\left(u = 1,2,...,U\right)$
M	Set of manufacturing plant $\left(m = 1,2,...,M\right)$
K	Set of technology (low, medium, high) $\left(k = 1,2,...,K\right)$
P	Set of battery type $\left(p = 1,2,...,P\right)$
O	Set of component type $\left(o = 1,2,...,O\right)$
T	Set of time periods $\left(t = 1,2,...,T\right)$
Decision variables	
QI_{pkirt}	Quantity of product p processed by technology k transported from customer i to repair center r during period t.
QR_{pkrut}	Quantity of product p processed by technology k transported from repair center r to collection and recycling center u during period t.
QU_{okumt}	Quantity of component o processed by technology k transported from collection and recycling center u to manufacturing plant m during period t.
x_{rk}	Equals 1 if repair center r is opened using technology k, otherwise 0.

y_{uk}	Equals 1 if collection and recycling center u is opened using technology k, otherwise 0.
CU_{pkut}	Quantity of product p disassembled using technology k at collection and recycling center u during period t.
Dependent variable	
IR_{pkrt}	Quantity of product p not yet repaired by technology k awaiting transfer at repair center r during period t.
IpU_{pkut}	End-of-period inventory of product p processed by technology k at collection and recycling center u during period t.
IoU_{okut}	End-of-period component inventory of product o processed by technology k at collection and recycling center u during period t.
Parameters	
CR_{pkrt}	Repair rate of product p using technology k at repair center r during period t.
S_{pkirt}	Maximum supply of product p from customers i to repair center r with technology k during period t.
A_{pko}	Transformation matrix representing the conversion of product p into component o using technology k at the collection and recycling point.
DM_{okmt}	Demand for component o processed by technology k at manufacturing plant m during period t.
FR_{rk}	Opening cost of repair center r with technology k.
FU_{uk}	Opening cost of collection and recycling center u with technology k.
VC_{pir}	Transportation cost for one unit of product p from customer i to repair center r.
VR_{pru}	Transportation cost for one unit of product p from repair center r to collection and recycling center u.
VU_{oum}	Transportation cost for component o from collection and recycling center u to manufacturing plant m.
IVR_{pr}	Inventory holding cost for unrepaired product p at repair center r.
IpV_{pu}	Inventory holding cost for pending product p at collection and recycling center u.
IoV_{ou}	Inventory holding cost for component o at collection and recycling center u.
FoR_{pr}	Ordering cost for product p from repair center r.
FoU_{ou}	Ordering cost for component o from collection and recycling center u.
EP_p	CO_2 emission cost per unit of product p *(unit/VND)* during transportation.
EO_o	CO_2 emission cost per unit of component o *(unit/VND)* during transportation.
ER_{pkr}	Emission cost per unit of product p processed by technology k at repair center r (unit/VND).
EU_{pku}	Emission cost per unit of product p processed by technology k at collection and recycling center u (unit/VND).
Big M	Big-M constant (very large).

Objective function

The objective of the model is to minimize the total cost of the system, including ordering costs O, inventory costs I, facility opening costs F and transportation costs between network nodes V, while also considering the environmental costs arising from emissions during the transportation and processing of products E.

$$MinC = O + I + F + V + E$$

The ordering cost *(O)* is the aggregation of various costs, including the cost of order processing, invoices, and order receipt/receiving.

$$O = \sum_{t\in T}\sum_{r\in R}\sum_{u\in U}\sum_{p\in P}\sum_{k\in K} FoR_{pr}.QR_{pkrut} + \sum_{t\in T}\sum_{u\in U}\sum_{m\in M}\sum_{o\in O}\sum_{k\in K} FoU_{ou}.QU_{okumt}$$

Inventory cost *(I)* includes the cost of storing products and components in the warehouse and warehouse operating costs.

$$I = \sum_{t\in T}\sum_{r\in R}\sum_{p\in P}\sum_{k\in K} \frac{(IR_{pkr,t-1} + IR_{pkrt})}{2}.IVR_{pr} + \sum_{t\in T}\sum_{u\in U}\sum_{p\in P}\sum_{k\in K} \frac{(IpU_{pku,t-1} + IpU_{pkut})}{2}.IpV_{pu} + \sum_{t\in T}\sum_{u\in U}\sum_{o\in O}\sum_{k\in K} \frac{(IoU_{oku,t-1} + IoU_{okut})}{2}.IoV_{ou}$$

Facility opening cost *(F)* includes the cost of renting premises and the cost of technology investment for the facility.

$$F = \sum_{r\in R}\sum_{k\in K} FR_{rk}.x_{rk} + \sum_{u\in U}\sum_{k\in K} FU_{uk}.y_{uk}$$

Transportation cost *(V)* includes the cost of trucks usage, labor cost and maintenance cost.

$$V = \sum_{t\in T}\sum_{i\in I}\sum_{r\in R}\sum_{k\in K}\sum_{p\in P} VC_{pir}.QI_{pkirt}.(1-CR_{pkrt})$$
$$+\sum_{t\in T}\sum_{r\in R}\sum_{u\in U}\sum_{p\in P}\sum_{k\in K} VR_{pru}.QR_{pkrut}$$
$$+\sum_{t\in T}\sum_{u\in U}\sum_{m\in M}\sum_{o\in O}\sum_{k\in K} VU_{oum}.QU_{okumt}$$

Environmental cost E, emission cost of components and products during transportation, and emission cost of components and products during processing.

$$E = \sum_{t\in T}\sum_{p\in P}\sum_{i\in I}\sum_{r\in R}\sum_{u\in U}\sum_{k\in K} EP_p.(QI_{pkirt}+QR_{pkrut})$$
$$+\sum_{t\in T}\sum_{o\in O}\sum_{u\in U}\sum_{m\in M}\sum_{k\in K} EO_o.QU_{okumt}$$
$$+\sum_{t\in T}\sum_{p\in P}\sum_{k\in K}\sum_{r\in R}\sum_{i\in I} ER_{pkr}.(1-CR_{pkrt}).QI_{pkirt}$$
$$+\sum_{t\in T}\sum_{p\in P}\sum_{k\in K}\sum_{u\in U} EU_{pku}.CU_{pkut}$$

Constraints

Constraint (1), (2), (3) state that the quantity of goods transported must not exceed the available stock at the warehouse.

$$\sum_{u\in U} QR_{pkrut} \le IR_{pkr,t-1} + \sum_{i\in I} QI_{pkirt}.\left(1-CR_{pkrt}\right) \quad (1)$$
$$\forall p\in P, \forall t\in T, \forall r\in R, \forall k\in K$$

$$CU_{pkut} \le IpU_{pku,t-1} + \sum_{r\in R} QR_{pkrut} \quad (2)$$
$$\forall p\in P, \forall u\in U, \forall k\in K, \forall t\in T$$

$$\sum_{m\in M} QU_{okumt} \le IoU_{oku,t-1} + \sum_{p\in P} A_{pko}.CU_{pkut} \quad (3)$$
$$\forall o\in O, \forall t\in T, \forall u\in U, \forall k\in K$$

Constraint (4), (5) specify that goods can only be delivered to the repair center and the recovery and recycling center if they are open.

$$\sum_{p\in P}\sum_{i\in I} QI_{pkirt} \le x_{rk}.M \quad \forall r\in R, \forall t\in T, \forall k\in K \quad (4)$$

$$\sum_{p\in P}\sum_{r\in R} QR_{pkrut} \le y_{uk}.M \quad \forall u\in U, \forall t\in T, \forall k\in K \quad (5)$$

Constraint (6), (8), (10) indicate that the inventory level at time period 0 (initially) is equal to 0. Constraint (7), (9), (11) ensure that the inventory is not lost or misplaced.

$$IR_{pkr,0} = 0 \quad \forall p\in P, \forall r\in R, \forall k\in K \quad (6)$$

$$IR_{pkrt} = IR_{pkr,t-1} - \sum_{u\in U} QR_{pkrut} + \sum_{i\in I} QI_{pkirt}.(1-CR_{pkrt}) \quad (7)$$
$$\forall p\in P, \forall r\in R, \forall k\in K, \forall t\in T, t\ne 0$$

$$IpU_{pku,0} = 0 \quad \forall p\in P, \forall u\in U, \forall k\in K \quad (8)$$

$$IpU_{pkut} = IpU_{pku,t-1} - CU_{pkut} + \sum_{r\in R} QR_{pkrut} \quad (9)$$
$$\forall p\in P, \forall u\in U, \forall k\in K, \forall t\in T, t\ne 0$$

$$IoU_{oku,0} = 0 \quad \forall o\in O, \forall u\in U, \forall k\in K \quad (10)$$

$$IoU_{okut} = IoU_{oku,t-1} - \sum_{m\in M} QU_{okumt} + \sum_{p\in P} A_{pko}.CU_{pkut} \quad (11)$$
$$\forall o\in O, \forall u\in U, \forall k\in K, \forall t\in T, t\ne 0$$

Constraints (12) and (13) ensure that a repair center or a recycling center can only be opened with one type of technology.

$$\sum_{k\in K} x_{rk} \le 1 \quad \forall r\in R \quad (12)$$

$$\sum_{k\in K} y_{uk} \le 1 \quad \forall u\in U \quad (13)$$

The constraint (14) states that the quantity of goods transported from the collection and recycling center u must meet the demand for component o of manufacturing plant m.

$$\sum_{u\in U}\sum_{o\in O} QU_{okumt} \ge \sum_{o\in O} DM_{okmt} \quad (14)$$
$$\forall m\in M, \forall k\in K, \forall t\in T$$

Constraint (15) ensures that the system's supply is determined and not exceeded.

$$QI_{pkirt} \le S_{pkirt} \quad (15)$$
$$\forall p\in P, \forall k\in K, \forall i\in I, \forall r\in R, \forall t\in T$$

Constraints (16 - 18) are constraints on variables, constraints on index sets, and input parameter constraints.

$$x_{rk}, y_{uk} \in \{0,1\} \quad (16)$$
$$\forall r\in R, \forall u\in U, \forall k\in K$$

$$QI_{pkirt}, QR_{pkrut}, QU_{okumt}, IR_{pkrt}, A_{pko}$$
$$IpU_{pkut}, IoU_{okut}, CU_{pkut}, DM_{okmt} \in \mathbb{R} \quad (17)$$
$$\forall i\in I, \forall r\in R, \forall u\in U, \forall m\in M,$$
$$\forall k\in K, \forall p\in P, \forall o\in O, \forall t\in T$$

$$FR_{rk}, FU_{uk}, VC_{pir}, VR_{pru}, VU_{oum}, IVR_{pr},$$
$$IpV_{pu}, IoV_{ou}, FoR_{pr}, FoU_{ou}, EP_p,$$
$$EO_o, ER_{pkr}, EU_{pku}, CR_{pkrt} \in \mathbb{R} \quad (18)$$
$$\forall i\in I, \forall r\in R, \forall u\in U, \forall m\in M,$$
$$\forall k\in K, \forall p\in P, \forall o\in O, \forall t\in T$$

5. Results and Discussion

The proposed optimization model is formulated as a Mixed-Integer Linear Programming (MILP) problem. This formulation is essential because the reverse logistics system design involves both strategic and operational decisions. Specifically, the model integrates continuous variables that govern the operational aspects (such as transportation flows and inventory levels) with binary variables that represent the strategic facility location and technology selection decisions. Due to its MILP structure, the model developed with a small dataset was optimally solved using the CPLEX Optimization Studio, an exact solution method that guarantees finding the global optimum. For larger, real-world instances, this problem is known to be NP-hard, which would necessitate the application of advanced heuristic or metaheuristic algorithms in future research.

5.1. Simulation Setup And Input Data

This study employs the 'Trial Handle' method to verify and evaluate the model. The model was developed and tested using IBM ILOG CPLEX Optimization Studio with the small input data set (Table 3).

Table 3. Number of indicators

Index	Number of indicators
I (customer nodes)	{1,2}
R (repair centers)	{1,2}
U (recycling centers)	{1,2}
M (manufacturing plants)	{1,2}
O (accessory)	{1,2}
P (product)	{1,2}
K (technology)	{1,2}
T (time periods)	{1, 2, 3}

The parameter data includes: transportation costs, inventory costs, facility opening costs, ordering costs, environmental costs, repair rate, product to component conver-sion matrix, etc., which are assigned values within a reasonable range to illustrate the model.

To ensure that the model is accurately built and tested in accordance with the formulated mathematical model, Excel is used to construct the model and verify the results obtained from CPLEX.

5.2. Model Optimization Results

The results from both CPLEX and Excel are identical, with the same objective function value (see Table 4):

Table 4. Results from CPLEX and manual verification using Excel

Criteria		Solve by hand (Excel)	CPLEX (OPL)
Objective value		MinC = 93,280	MinC = 93,280
Decision variable	x_{rk}	$x_{11}, x_{22} = 1$	$x_{11}, x_{22} = 1$
		$x_{12}, x_{21} = 0, \dots$	$x_{12}, x_{21} = 0, \dots$
	y_{uk}	$y_{11}, y_{22} = 1$	$y_{11}, y_{22} = 1$
		$y_{12}, y_{21} = 0, \dots$	$y_{12}, y_{21} = 0, \dots$
Satisfied constraints		232/232	232/232
Solution time		-	00:00:00:54

To gain a more comprehensive view, several alternative solutions are input into the model in Excel to verify the objective function when optimized using CPLEX.

The proposed MILP model was solved using IBM ILOG CPLEX Optimization Studio 22.1. All computational experiments were performed on a personal computer equipped with an Intel® Core™ i5-1235U CPU (up to 4.4 GHz, 10 cores and 12 threads), 16 GB DDR4 RAM (2666 MHz), and a 512 GB NVMe SSD running Windows 11 Home (64-bit) operating system.

Table 5. Statistics of parameters when solving with CPLEX.

Statictis		Value
Constraints		232
Variables		248
	Binary	8
	Interger	240
	Non-zero coefficients	920
Iterations		285
Solution pool		
	Count	1
	Mean objective	93,280

From the table above, it can be observed that the alternative solutions, when input into the model, yield objective function values that are not as optimal as the one obtained through optimization using CPLEX.

These results demonstrate the reliability and optimality of the constructed model. When comparing the Optimal Solution from the optimization solver with other manually generated solutions entered via Excel, it is evident that although all alternative approaches satisfy 232 out of 232 constraints, only the solver's solution achieves the lowest objective function value of 93,280. The remaining solutions yield objective values starting from 93,280, confirming that the model not only ensures feasibility but also identifies the truly optimal solution.

This confirms the mathematical soundness and the practical applicability of the model in designing a reverse logistics system for electric vehicle batteries.

Finally, constructing a real world dataset from battery manufacturers, recycling centers, or logistics enterprises would help better calibrate the model and lay the groundwork for real world pilot implementation in the near future.

6. Conclusion

This study proposes an optimization model for battery reverse logistics, focusing on facility location, inventory management, and transportation planning. By integrating sustainability into the Inventory-Location Problem (ILP), the model addresses both economic and environmental concerns. The contributions of the battery recovery system design model can be summarized as follows: (i) supporting strategic decision-making regarding the location and number of recovery facilities to minimize fixed costs; (ii) optimizing transportation flows between facilities and collection points to reduce logistics costs and carbon emissions; (iii) balancing inventory at intermediate points to mitigate safety risks and lower storage costs; and (iv) providing a quantitative analytical framework that enables the development of various scenarios, allowing the system to better adapt to fluctuations in supply and recycling demand. These contributions not only enhance operational efficiency but also promote sustainability throughout the entire reverse logistics chain of batteries.

The results demonstrate that strategic facility placement significantly reduces transportation distances, leading to lower logistics costs and improved responsiveness in the recovery and recycling of waste batteries. Furthermore, by integrating environmental cost components such as carbon emissions from transportation and processing the model supports environmentally conscious decision-making and aligns with global efforts toward sustainable supply chain management.

The model's applicability extends beyond EV batteries, as it can be generalized to other electronic waste and further refined by integrating uncertainty factors or multi-layer network structures. Successful real-world implementation necessitates accurate, actual data on waste battery flows, operating costs, and environmental factors. Furthermore, deploying the system demands significant investment in resources, including collection and recycling infrastructure, safe battery treatment technologies, a well-trained workforce, and dedicated optimization software and tools. However, several critical barriers threaten practical implementation despite the clear benefits. From a policy and legal standpoint, regulations governing battery waste remain fragmented, compliance costs are high, and vital incentive mechanisms (such as financial support or extended producer responsibility) have not been fully enforced, limiting business motivation. Coordinating stakeholders is complex due to the uneven distribution of benefits, restricted data sharing stemming from competitive concerns, and the inherent instability of discarded battery flows. Lastly, social challenges persist, as public awareness regarding environmental hazards is low and widespread consumer habits for returning used batteries have not yet been established. These collective issues require targeted solutions, including improved policies, the establishment of transparent and equitable collaboration mechanisms, and enhanced public awareness campaigns to enable the effective operation of the battery recovery system.

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