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Research article

A comprehensive bi-objective optimization model to design circular supply chain networks for sustainable electric vehicle batteries

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Abstract: As electric vehicles (EVs) continue to advance, there is a growing emphasis on sustainability, particularly in the area of effectively managing the lifecycle of EV batteries. In this study, an efficient and novel optimization model was proposed for designing a circular supply chain network for EV batteries. In doing so, a comprehensive, bi-objective, mixed-integer linear programming model was employed. It is worth noting that the current model outlined in this paper involved both forward and reverse flows, illustrating the process of converting used batteries into their constituent materials or repurposing them for various applications. In line with the circular economy concept, the current model also minimized the total costs and carbon emission to develop an inclusive optimization framework. The LP-metric method was applied to solve the presented bi-objective optimization model. We simulated six problems with different sizes using data and experts' knowledge of a lithium-ion battery manufacturing industry in Canada, and evaluated the performance of the proposed model by simulated data. The results of the sensitivity analysis process of the objective functions coefficients showed that there was a balance between the two objective functions, and the costs should be increased to achieve lower emissions. In addition, the demand sensitivity analysis revealed that the increase in demand directly affects the increase in costs and emissions.

Keywords: circular economy; sustainable supply chain; electric vehicle battery; optimization; LP-metric method

1. Introduction

When it comes to sustainability in transportation, electric vehicle (EV) batteries are assigned much attention and are supposed to transform the automotive industry. Today, the whole world is thinking about how to counterattack global warming and climate change and how to minimize greenhouse gas emissions. In this light, EVs enter the scenario to solve the issue since their application may lead to the creation of a more environmentally friendly context [1]. Indeed, EV batteries are placed in the focal center of this technological transformation as they enable emission-free mobility. These batteries make a great contribution to sustainable transportation since they prepare the needed energy sources for powering EVs and eliminate the need for fossil fuels [2].

There is a noticeable ecological footprint from EV battery production to their use in emission-free vehicles. It is noteworthy that the processing of raw materials, including nickel, lithium, and cobalt for battery production often brings environmental and social challenges [3,4]. In addition, the manufacturing scenarios pertaining to battery production may lead to the emission of carbon and some other polluting elements. Although EVs are significantly less polluting than other alternatives, this environmental superiority may sometimes be ignored at the cost of the energy and resource necessary in the process of battery manufacturing [5]. Moreover, the end-of-life phase is another challenge since the inappropriate disposal or ineffective recycling of these batteries may result in the production of highly dangerous wastes and their release into the environment [6]. Suitable supply chain measures should be taken in this area to eliminate these adverse environmental consequences and develop sustainable criteria. Therefore, there is a pressing need for the development of a circular supply chain approach that contains proper recycling, eco-friendly manufacturing, responsible sourcing, and suitable disposal methods [7].

The circular supply chain, in the scope of EV batteries, has come into play as a transformative and revolutionary approach that calls for an updated version of sustainability [8]. A circular supply chain is beyond a linear approach and, indeed, is an interconnected series of processes whose aim is to opt for resource optimization, reduction of waste production, and improvement of closed-loop systems [9]. This concept receives a high status within the scope of EV batteries since it provides a desirable opportunity to cope with the adverse environmental impacts arising from the production, use, and end-of-life of EV batteries [10].

When great value is assigned to circularity, the conventional model of "take-make-dispose" can be replaced by another system with the capability of efficient recycling, recovery, and reuse of battery materials. In this inclusive approach, the whole lifespan of EVs is taken into account from the preparation of raw materials for their production to their application in vehicles and end-of-life [11].

If EV batteries are carefully designed and manufactured, each phase of their lifecycle comes out with the least possible loss of useful resources and the highest possible degree of sustainability [12]. This involves adopting practices such as efficient sourcing of raw materials, waste reduction, reduced energy consumption, and the integration of the intended chain process from collection and refurbishment to the recycling of used batteries [13,14].

The unanimous practices and cooperation of multiple stakeholders is needed to appropriately develop circularity within the realm of EV batteries. In this area, battery manufacturers should employ eco-design tenets to make disassembly and reuse easy, and vehicle manufacturers should be required to provide an accommodation of battery maintenance, replacement, and recycling. In the same way, battery recyclers should be responsible for the development of an effective and environmentally friendly roadmap for the extraction of useful materials from end-of-life batteries. Additionally, policymakers should adopt proper rules and regulations that support sustainability and economic circularity [15].

Another challenge in this area pertains to integrating mathematical programming models in the development of a desired circular supply chain for EVs as it is a great step to transitioning toward sustainability and circularity in the scope of battery production. Policymakers can have permission to direct the complex framework of economic circularity when mathematical optimization techniques are managed appropriately and effectively. This leads to the unity of waste reduction, resource use, and closed-loop systems. The output can be the emergence of a quantitative framework through which one can analyze different elements and processes in this domain, including inventory management, production capacity, recycling process, and transportation routes. Finally, cost-effectiveness, minimized environmental pollution, and greenness will be there. With the application of multi-objective solution approaches, conflicting goals like simultaneous efficient resource use and minimized carbon emissions can be balanced, which can finally be directed toward the development of a desirable circular supply chain for EV batteries.

The literature review shows that one of the most widely used tools in closed-loop/circular supply chain network configuration is the mathematical programming tool that has been employed in various industries, such as the healthcare industry [16–18], textile industry [19,20], automotive industry [21–23], lead acid battery industry [24–26], plastic industry [27], food industry [28,29], agriculture industry [30–32], and tire industry [33–35].

In Table 1, our work is compared with existing papers to show the research gap. The literature review shows that there is only one article (i.e., Tavana et al. [11]) that has used the mathematical programming tool to structure a circular supply chain in the EV battery industry. For this purpose, Tavana et al. [11] developed a bi-objective mixed-integer linear programming (MILP) model to make optimal decisions in the EV battery industry by considering circularity. Although they consider both forward and reverse flows, their network was structured in a general form and lacked alignment with real-world scenarios. They have assumed that all retired batteries can be refurbished and after processing can be used as EV batteries, which is not necessarily the case. In practical scenarios, retired EV batteries are categorized into three groups. The first group consists of batteries with sufficient remaining capacity, suitable for use in the manufacturing of second-hand EV batteries. The second group encompasses batteries repurposed for backup power or energy storage applications. The third group involves batteries with low remaining capacity, considered cost-ineffective for reuse and necessitating recycling. According to our best knowledge, in this study, for the first time, a comprehensive bi-objective MILP model is formulated to structure a circular supply chain to optimize strategic and operational decisions in the EV battery industry. The proposed model reflects an accurate view of the real world in the EV battery industry by structuring operations with details. Overall, the key contributions of this study include:

- Developing a comprehensive bi-objective MILP model to manage new and retired EV batteries considering different recycling technologies;
- Applying an LP-metric method to minimize total costs and CO2 emissions simultaneously in both forward and reverse flows of the network;

- Investigating the effectiveness of the presented bi-objective MILP model using simulated data derived from the real world.

Table 1. Comparison of the current study with some existing papers.

	Model type	Multi-product	Multi-period	Multi-objective	Facility location	Forward flow	Reverse flow	Recycling technology	Heterogenous vehicles	Circular economy	Environmental issues	Supplier selection	Order allocation	Centers: Manufacturing	Centers: Collection	Centers: Refurbishment	Centers: Recycling	Centers: Disposal	EV battery industry
[27]	MILP	√	√	√	√	√	√	-	-	-	-	√	√	√	√	-	√	-	-
[36]	MILP	√	√	√	√	√	√	-	√	-	√	√	√	√	√	√	-	√	-
[34]	MILP	√	-	√	√	√	√	√	-	-	√	√	√	√	-	-	√	-	-
[24]	MILP	-	-	√	√	√	√	-	-	-	√	-	-	√	√	-	√	√	-
[17]	MILP	√	√	√	√	√	√	-	-	-	-	√	√	√	-	-	√	-	-
[33]	MILP	√	√	√	√	√	√	-	-	-	√	√	√	√	√	√	-	√	-
[21]	MILP	-	-	√	√	√	√	-	√	-	√	√	√	√	√	√	√	√	-
[19]	MILP	√	√	√	√	√	√	-	-	-	√	√	√	√	√	√	√	√	-
[31]	MILP	√	√	√	√	√	√	-	-	√	√	-	-	√	-	-	√	-	-
[32]	MILP	√	√	√	√	√	√	-	-	√	√	√	√	√	√	-	√	-	-
[9]	MILP	√	√	√	√	√	√	-	√	√	√	√	√	√	√	-	√	√	-
[11]	MILP	√	√	√	√	√	√	-	√	√	√	-	-	√	√	-	-	-	√
This study	MILP	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√

The rest of this study is organized as follows. The problem statement and proposed MILP model are presented in Section 2. Section 3 is allocated to the results. Sensitivity analysis and managerial implications are presented in Sections 4 and 5, respectively. Finally, the conclusion is provided in Section 6.

2. Problem statement and proposed model

In this section, a bi-objective mathematical model is formulated to manage the production, distribution, recycling, and disposal of EV batteries in a circular supply chain network. EV battery assembly centers buy cells from suppliers and produce all kinds of EV batteries, then sending them to demand points. Retired EV batteries are collected from demand points by collection centers. In collection centers, retired EV batteries are divided into three groups. The first group are batteries that have the potential to be used in the EV battery industry. This group of batteries are sent to the EV battery assembly center. The second group are batteries that are not suitable for use in EV batteries, but are effective for providing backup power, energy storage, etc. This group of batteries should be transferred to a second life EV battery production center. Note that the second group of batteries is divided into two categories. The first category are batteries used for forklifts and heavy vehicles, and the second category are batteries that are utilized in the production of energy storage batteries. The third group of retired EV batteries are unusable and must be recycled. These batteries are broken down into their components. The components that can be recycled are processed in recycling centers, and the rest of them will be disposed. It should be noted that the recycled components are sold to suppliers. The general structure of the investigated network is depicted in Figure 1.

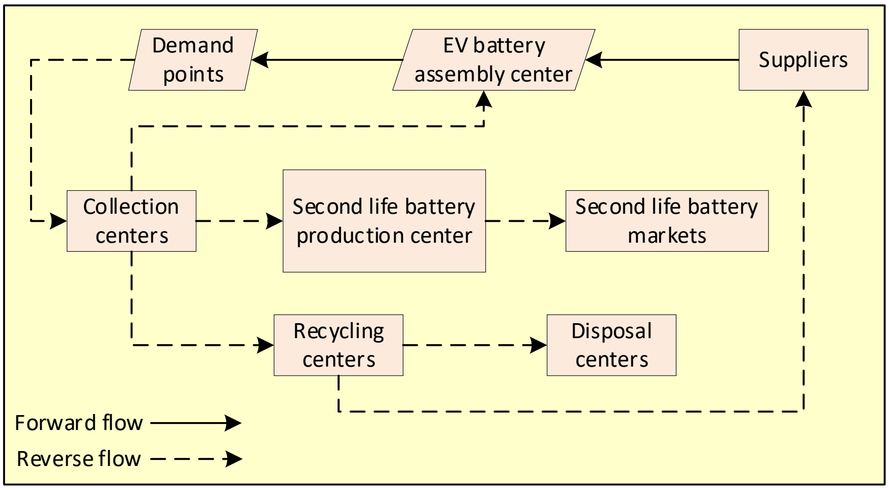

Figure 1. The investigated network.

The objectives of this model are to minimize total costs and CO2 emission simultaneously. Network costs are divided into two categories, including strategic and operational costs. Note that processing costs in centers, costs of purchasing cells, transportation costs, and ordering costs are considered operating costs, and setup costs are considered strategic costs. We have assumed that these costs are the influential costs in structuring the supply chain network of EV batteries.

It should be noted that the implementation of a circular economy in any industry is always associated with barriers and challenges, such as a lack of funds, infrastructure limitations, etc. Researchers who use mathematical programming tools to design circular supply chain networks assume that there are no barriers to implementing a circular economy [9,11,37]. In other words, circular supply chain network design happens when barriers are removed. In this research, as in the papers presented in the literature, it is assumed that the barriers to the implementation of a circular economy in the EV battery industry have been removed. The assumptions of the presented optimization model are given below:

- The proposed model is multi-product and multi-period, and considers forward and reverse flows in the network design.
- There is one EV battery assembly center.
- Collection, second life EV battery production, recycling, and disposal centers are located by the model.
- Suppliers, collection, second life EV battery production, recycling, disposal centers, and vehicles are capacitated.
- Vehicles are heterogeneous.
- Shortages in demand points are not allowed.

Mathematical Model

Indices

$p \in \{1,2,...,P\}$	Component
$b \in \{1,2,...,B\}$	EV battery

$q \in \{1, 2, ..., Q\}$	Cell
$d \in \{1, 2, ..., D\}$	Demand point
$c \in \{1, 2, ..., C\}$	Collection center
$s \in \{1, 2, ..., S\}$	Second life EV battery production center
$g \in \{1, 2, ..., G\}$	Supplier
$r \in \{1, 2, ..., R\}$	Recycling center
$e \in \{1, 2, ..., E\}$	Recycling technology
$f \in \{1, 2, ..., F\}$	Disposal center
$v \in \{1, 2, ..., V\}$	Vehicle
$t \in \{1, 2, ..., T\}$	Time period

Parameters

δ_{bt}^{ASS}	The cost of assembling the type *b* EV battery in time period *t*
δ_{bct}^{CL}	The cost of processing the type *b* EV battery at collection center *c* in time period *t*
δ_{bst}^{SL}	The cost of refurbishing the type *b* EV battery at second life EV battery production center *s* in time period *t*
δ_{bret}^{RC}	The average cost of recycling the components of the type *b* EV battery at recycling center *r* using recycling technology *e* in time period *t*
δ_{pft}^{DS}	The average cost of disposing of component *p* at disposal center *f* in time period *t*
δ_{qgt}^{SP}	The purchase price of one unit of a type *q* cell from supplier *g* in time period *t*
λ_{pgt}^{SP}	The suggested price of supplier *g* for buying each unit of component *p* in time period *t*
λ_{bt}^{MR-I}	The selling price of the type *b* second life EV battery categorized in group I at the market in time period *t*
λ_{bt}^{MR-II}	The selling price of the type *b* second life EV battery categorized in group II at the market in time period *t*
ϑ_{g}^{SP-ASS}	The distance between the supplier *g* and the EV battery assembly center
ϑ_{d}^{ASS-DM}	The distance between the EV battery assembly center and the demand point *d*
ϑ_{dc}^{DM-CL}	The distance between the demand point *d* and the collection center *c*
ϑ_{c}^{CL-ASS}	The distance between the collection center *c* and the EV battery assembly center
ϑ_{cs}^{CL-SL}	The distance between the collection center *c* and second life EV battery production center *s*
ϑ_{gs}^{SP-SL}	The distance between the supplier *g* and the second life EV battery production center *s*
ϑ_{cr}^{CL-RC}	The distance between the collection center *c* and the recycling center *r*
ϑ_{s}^{SL}	The distance between the second life EV battery production center *s* and the second life EV battery market
ϑ_{rf}^{RC-DS}	The distance between the recycling center *r* and the disposal center *f*
ϑ_{rg}^{RC-SP}	The distance between the recycling center *r* and the supplier *g*
κ_{qgt}^{SP}	The capacity of the supplier *g* to supply a type *q* cell in time period *t*

κ_c^{CL}	The capacity of the collection center *c* for processing the EV batteries
κ_s^{SL}	The capacity of the second life EV battery production center *s*
κ_{re}^{RC}	The capacity of the type *e* recycling technology at recycling center *r*
κ_f^{DS}	The capacity of the disposal center *f*
κ_v^{VH}	The capacity of the vehicle *v*
α_{gt}^{SP}	The cost of ordering the supplier *g* to purchase the cells in time period *t*
α_c^{CL}	The cost of establishing the collection center *c*
α_{rt}^{RC}	The cost of ordering to the recycling center *r* in time period *t*
α_{ft}^{DS}	The cost of ordering to the disposal center *f* in time period *t*
α_s^{SL}	The cost of establishing the second life EV battery production center *s*
β_{bdt}	The demand of the demand point *d* for the type *b* EV battery in time period *t*
ξ_{vt}	Cost of shipping for each unit distance by the vehicle *v*
WG_b^1	Weight of the type *b* EV battery
WG_q^2	Weight of the type *q* cell
Φ_{pbe}	Rate of the type *p* component extracted from the type *b* EV battery using type *e* recycling technology
CO_{be}^{RC}	The average amount of CO2 emitted for recycling components of the type *b* EV battery by type *e* recycling technology
CO_v^{VH}	The average amount of CO2 emitted by vehicle *v* per unit of distance
γ_{pb}	The amount of the type *p* component used in the type *b* EV battery
φ_{qb}^1	The number of type *q* cells required to make one unit of the type *b* EV battery
φ_{qb}^2	The average number of type *q* cells required to refurbish one unit of the type *b* EV battery usable in EVs
φ_{qb}^3	The average number of type *q* cells required to make one unit of the type *b* second life EV battery categorized in group I
φ_{qb}^4	The average number of type *q* cells required to make one unit of the type *b* second life EV battery categorized in group II
RB_{bdt}	The number of type *b* retired EV batteries at demand point *d* in time period *t*
ψ_b^{RC}	Rate of the type *b* EV battery sent to the recycling centers
ψ_b^{ASS}	Rate of the type *b* EV battery sent to the EV assembly center
ψ_b^{SL}	Rate of the type *b* EV battery sent to the second life battery production centers to make the type I second life EV battery
M	A large number

Variables

U_{gt}^{SP} $\begin{cases} 1 & \text{In case of selecting the supplier } g \text{ to purchase the cells in time period } t \\ 0 & \text{Otherwise} \end{cases}$

U_c^{CL} $\begin{cases} 1 & \text{In case of establishing the collection center } c \text{ in time period } t \\ 0 & \text{Otherwise} \end{cases}$

U_s^{SL} $\begin{cases} 1 & \text{In case of establishing the second life EV battery production center } s \end{cases}$

		Otherwise
U_{ret}^{RC}	$\begin{cases}1\\0\end{cases}$	In case of selecting the recycling center *r* with type *e* technology in time period *t* Otherwise
U_{ft}^{DS}	$\begin{cases}1\\0\end{cases}$	In case of selecting the disposal center *f* in time period *t* Otherwise
N_{gvt}^{SP-ASS}		The minimum number of vehicles *v* used to ship the cells from the supplier *g* to the EV battery assembly center in time period *t*
N_{dvt}^{ASS-DM}		The minimum number of vehicles *v* used to ship the EV batteries from the EV battery assembly center to the demand point *d* in time period *t*
N_{dcvt}^{DM-CL}		The minimum number of vehicles *v* used to ship the EV batteries from the demand point *d* to the collection center *c* in time period *t*
N_{cvt}^{CL-ASS}		The minimum number of vehicles *v* used to ship the EV batteries from the collection center *c* to the EV battery assembly center in time period *t*
N_{csvt}^{CL-SL}		The minimum number of vehicles *v* used to ship the EV batteries from the collection center *c* to the second life EV battery production center *s* in time period *t*
N_{gsvt}^{SP-SL}		The minimum number of vehicles *v* used to ship the cells from the supplier *g* to the second life EV battery production center *s* in time period *t*
N_{crvt}^{CL-RC}		The minimum number of vehicles *v* used to ship the EV batteries from the collection center *c* to the recycling center *r* in time period *t*
N_{svt}^{SL-I}		The minimum number of vehicles *v* used to ship the type I second life EV batteries from the second life EV battery production center *s* to the market in time period *t*
N_{svt}^{SL-II}		The minimum number of vehicles *v* used to ship the type II second life EV batteries from the second life EV battery production center *s* to the market in time period *t*
N_{rfvt}^{RC-DS}		The minimum number of vehicles *v* used to ship the components from the recycling center *r* to the disposal center *f* in time period *t*
N_{rgvt}^{RC-SP}		The minimum number of vehicles *v* used to ship the components from the recycling center *r* to the supplier *g* in time period *t*
W_{qgt}^{SP-ASS}		The number of type *q* cells purchased from the supplier *g* by the EV battery assembly center in time period *t*
$W_{qgt}^{SP-ASS-I}$		The number of type *q* cells purchased from the supplier *g* by the EV battery assembly center to make new EV batteries in time period *t*
$W_{qgt}^{SP-ASS-II}$		The number of type *q* cells purchased from the supplier *g* by the EV battery assembly center to make refurbished EV batteries in time period *t*
W_{bdt}^{ASS-DM}		The number of type *b* EV batteries shipped from the EV battery assembly center to the demand point *d* in time period *t*
W_{bdct}^{DM-CL}		The number of type *b* retired EV batteries shipped from the demand point *d* to the collection center *c* in time period *t*
W_{bct}^{CL-ASS}		The number of type *b* EV batteries shipped from the collection center *c* to the EV battery assembly center in time period *t*
W_{bcst}^{CL-SL}		The number of type *b* EV batteries shipped from the collection center *c* to the second life EV battery production center *s* in time period *t*
W_{qgst}^{SP-SL}		The number of type *q* cells shipped from the supplier *g* to the second life EV battery production center *s* in time period *t*
W_{bcrt}^{CL-RC}		The number of type *b* EV batteries shipped from the collection center *c* to the recycling center *r* in time period *t*

W_{bst}^{SL-I} The number of type b second life EV batteries categorized in group I shipped from the second life EV battery production center s to the market in time period t

W_{bst}^{SL-II} The number of type b second life EV batteries categorized in group II shipped from the second life EV battery production center s to the market in time period t

W_{prft}^{RC-DS} The amount of type p components shipped from the recycling center r to the disposal center f in time period t

W_{prgt}^{RC-SP} The amount of type p components shipped from the recycling center r to the supplier g in time period t

W_{bret}^{RC} The number of type b EV batteries recycled at the recycling center r using the type e technology in time period t

Objective functions

$$\begin{aligned}
Min\ Z_1 = & \sum_{b,d,t} \delta_{bt}^{ASS} \times W_{bdt}^{ASS-DM} + \sum_{b,d,c,t} \delta_{bct}^{CL} \times W_{bdct}^{DM-CL} + \sum_{b,c,s,t} \delta_{bst}^{SL} \times W_{bcst}^{CL-SL} + \\
& \sum_{b,c,r,e,t} \delta_{bret}^{RC} \times W_{bcrt}^{CL-RC} + \sum_{p,r,f,t} \delta_{pft}^{DS} \times W_{prft}^{RC-DS} + \sum_{q,g,t} \delta_{qgt}^{SP} \times W_{qgt}^{SP-ASS} + \\
& \sum_{q,g,s,t} \delta_{qgt}^{SP} \times W_{qgst}^{SP-SL} + \sum_{g,t} \alpha_{gt}^{SP} \times U_{gt}^{SP} + \sum_{c} \alpha_{c}^{CL} \times U_{c}^{CL} + \sum_{r,e,t} \alpha_{rt}^{RC} \times U_{ret}^{RC} + \\
& \sum_{f,t} \alpha_{ft}^{DS} \times U_{ft}^{DS} + \sum_{s} \alpha_{s}^{SL} \times U_{s}^{SL} + \sum_{g,v,t} \xi_{vt} \times \vartheta_{g}^{SP-ASS} \times N_{gvt}^{SP-ASS} + \\
& \sum_{d,v,t} \xi_{vt} \times \vartheta_{d}^{ASS-DM} \times N_{dvt}^{ASS-DM} + \sum_{d,c,v,t} \xi_{vt} \times \vartheta_{dc}^{DM-CL} \times N_{dcvt}^{DM-CL} + \\
& \sum_{c,v,t} \xi_{vt} \times \vartheta_{c}^{CL-ASS} \times N_{cvt}^{CL-ASS} + \sum_{c,s,v,t} \xi_{vt} \times \vartheta_{cs}^{CL-SL} \times N_{csvt}^{CL-SL} + \\
& \sum_{s,v,t} \xi_{vt} \times \vartheta_{s}^{SL} \times (N_{svt}^{SL-I} + N_{svt}^{SL-II}) + \sum_{r,f,v,t} \xi_{vt} \times \vartheta_{rf}^{RC-DS} \times N_{rfvt}^{RC-DS} + \\
& \sum_{r,g,v,t} \xi_{vt} \times \vartheta_{rg}^{RC-SP} \times N_{rgvt}^{RC-SP} - \sum_{p,r,g,t} \lambda_{pgt}^{SP} \times W_{prgt}^{RC-SP} - \sum_{b,s,t} \lambda_{bt}^{MR-I} \times W_{bst}^{SL-I} - \\
& \sum_{b,s,t} \lambda_{bt}^{MR-II} \times W_{bst}^{SL-II}
\end{aligned} \tag{1}$$

The first objective function minimizes the total costs of the network. These costs include the cost of assembling the EV batteries, the cost of processing the EV batteries at the collection centers, the cost of refurbishing the EV batteries at the second life EV battery production centers, the cost of recycling and disposing of the EV batteries, the cost of purchasing the cells from the suppliers, the cost of ordering to the suppliers, the cost of establishing the collection centers, the cost of ordering to the recycling and disposal centers, the cost of establishing the second life EV battery production centers, and the cost of transportation, respectively. It should be noted that the income from the sale of components to suppliers and the sale of second life EV batteries categorized in group I and II in the market is deducted from the total cost of the network.

$$Min\ Z_2 = \sum_{g,v,t} CO_v^{VH} \times \vartheta_g^{SP-ASS} \times N_{gvt}^{SP-ASS} + \sum_{d,v,t} CO_v^{VH} \times \vartheta_d^{ASS-DM} \times N_{dvt}^{ASS-DM} +$$
$$\sum_{d,c,v,t} CO_v^{VH} \times \vartheta_{dc}^{DM-CL} \times N_{dcvt}^{DM-CL} + \sum_{c,v,t} CO_v^{VH} \times \vartheta_c^{CL-ASS} \times N_{cvt}^{CL-ASS} +$$
$$\sum_{c,s,v,t} CO_v^{VH} \times \vartheta_{cs}^{CL-SL} \times N_{csvt}^{CL-SL} + \sum_{s,v,t} CO_v^{VH} \times \vartheta_s^{SL} \times (N_{svt}^{SL-I} + N_{svt}^{SL-II}) + \tag{2}$$
$$\sum_{r,f,v,t} CO_v^{VH} \times \vartheta_{rf}^{RC-DS} \times N_{rfvt}^{RC-DS} + \sum_{r,g,v,t} CO_v^{VH} \times \vartheta_{rg}^{RC-SP} \times N_{rgvt}^{RC-SP} + \sum_{b,r,e,t} CO_{be}^{RC} \times W_{bret}^{RC}$$

The second objective function deals with the minimization of CO2 emissions caused by the transportation and recycling of the EV battery components.

subject to:

$$N_{gvt}^{SP-ASS} \geq \frac{\sum_q W_{qgt}^{SP-ASS} \times WG_q^2}{\kappa_v^{VH}} \qquad \forall g,v,t \tag{3}$$

The minimum number of vehicles required to transport cells from the suppliers' locations to the EV battery assembly center is calculated by constraint (3). Both objective functions are minimized and include the variable N_{gvt}^{SP-ASS}. This leads to the calculation of the smallest integer value greater than $\frac{\sum_q W_{qgt}^{SP-ASS} \times WG_q^2}{\kappa_v^{VH}}$ for the variable N_{gvt}^{SP-ASS}.

$$N_{dvt}^{ASS-DM} \geq \frac{\sum_b W_{bdt}^{ASS-DM} \times WG_b^1}{\kappa_v^{VH}} \qquad \forall d,v,t \tag{4}$$

With an argument similar to constraint (3), the minimum number of vehicles required to transport EV batteries from the EV battery assembly center to the demand points is determined by constraint (4).

$$N_{dcvt}^{DM-CL} \geq \frac{\sum_b W_{bdct}^{DM-CL} \times WG_b^1}{\kappa_v^{VH}} \qquad \forall d,c,v,t \tag{5}$$

Constraint (5) determines the minimum number of vehicles required to transport EV batteries from the demand points to collection centers.

$$N_{cvt}^{CL-ASS} \geq \frac{\sum_b W_{bct}^{CL-ASS} \times WG_b^1}{\kappa_v^{VH}} \qquad \forall c,v,t \tag{6}$$

$$N_{csvt}^{CL-SL} \geq \frac{\sum_b W_{bcst}^{CL-SL} \times WG_b^1}{\kappa_v^{VH}} \qquad \forall c,s,v,t \tag{7}$$

$$N_{crvt}^{CL-RC} \geq \frac{\sum_b W_{bcrt}^{CL-RC} \times WG_b^1}{\kappa_v^{VH}} \qquad \forall c,r,v,t \tag{8}$$

Constraints (6) to (8) calculate the minimum number of vehicles required to transport the EV batteries from the collection centers to the EV battery assembly centers, second life EV battery production centers, and recycling centers, respectively.

$$N_{gsvt}^{SP-SL} \geq \frac{\sum_{q} W_{qgst}^{SP-SL} \times WG_{q}^{2}}{\kappa_{v}^{VH}} \qquad \forall g,s,v,t \tag{9}$$

The minimum number of vehicles required to transport cells from the suppliers' locations to the second life EV battery production centers is determined by constraint (9).

$$N_{svt}^{SL-I} \geq \frac{\sum_{b} W_{bst}^{SL-I} \times WG_{b}^{1}}{\kappa_{v}^{VH}} \qquad \forall s,v,t \tag{10}$$

$$N_{svt}^{SL-II} \geq \frac{\sum_{b} W_{bst}^{SL-II} \times WG_{b}^{1}}{\kappa_{v}^{VH}} \qquad \forall s,v,t \tag{11}$$

Constraints (10) and (11) calculate the minimum number of vehicles required to transport the type I and II second life EV batteries from the second life EV battery production centers to the market, respectively.

$$N_{rfvt}^{RC-DS} \geq \frac{\sum_{p} W_{prft}^{RC-DS}}{\kappa_{v}^{VH}} \qquad \forall r,f,v,t \tag{12}$$

$$N_{rgvt}^{RC-SP} \geq \frac{\sum_{p} W_{prgt}^{RC-SP}}{\kappa_{v}^{VH}} \qquad \forall r,g,v,t \tag{13}$$

Constraints (12) and (13) determine the minimum number of vehicles required to transport the components from the recycling center to the disposal centers and suppliers, respectively.

$$W_{qgt}^{SP-ASS} + \sum_{s} W_{qgst}^{SP-SL} \leq \kappa_{qgt}^{SP} \times U_{gt}^{SP} \qquad \forall q,g,t \tag{14}$$

Constraint (14) states that the number of cells shipped from each supplier to the EV battery assembly center and the second life EV battery production centers should not exceed the capacity of that supplier.

$$\sum_{b,d} W_{bdct}^{DM-CL} \leq \kappa_{c}^{CL} \times U_{c}^{CL} \qquad \forall c,t \tag{15}$$

$$\sum_{b,c} W_{bcst}^{CL-SL} \leq \kappa_{s}^{SL} \times U_{s}^{SL} \qquad \forall s,t \tag{16}$$

$$\sum_{b} W_{bret}^{RC} \leq \kappa_{re}^{RC} \times U_{ret}^{RC} \qquad \forall r,e,t \tag{17}$$

$$\sum_{p,r} W_{prft}^{RC-DS} \leq \kappa_{f}^{DS} \times U_{ft}^{DS} \qquad \forall f,t \tag{18}$$

Non-exceeding the capacity of the collection, the second life EV battery production, the recycling, and the disposal centers are presented in constraints (15) to (18), respectively.

$$W_{qgt}^{SP-ASS} = W_{qgt}^{SP-ASS-I} + W_{qgt}^{SP-ASS-II} \qquad \forall q,g,t \tag{19}$$

Cells purchased from suppliers by the EV battery assembly center are used to produce new and refurbished EV batteries. This issue is considered in constraint (19).

$$W_{qgt}^{SP-ASS-II} = 0 \qquad \forall q,g,t=1 \tag{20}$$

In the first time period, the refurbished EV batteries are not produced in the assembly center. Therefore, the cells purchased for the production of refurbished EV batteries in this period should be zero. Constraint (20) guarantees this.

$$\sum_{q,g} \frac{W_{qgt}^{SP-ASS-I}}{\varphi_{qb}^{1}} = \sum_{d} W_{bdt}^{ASS-DM} \qquad \forall b,t=1 \tag{21}$$

$$\sum_{q,g} \frac{W_{qgt}^{SP-ASS-I}}{\varphi_{qb}^{1}} + \sum_{c} W_{bct}^{CL-ASS} = \sum_{d} W_{bdt}^{ASS-DM} \qquad \forall b,t>1 \tag{22}$$

The inventory balance at the EV battery assembly center for the first time period and subsequent periods are shown in constraints (21) and (22), respectively.

$$\sum_{b,c} W_{bct}^{CL-ASS} \times \varphi_{qb}^{2} = \sum_{g} W_{qgt}^{SP-ASS-II} \qquad \forall q,t \tag{23}$$

Constraint (24) shows the relationship between the number of EV batteries shipped from collection centers to the assembly center and the number of cells purchased from suppliers to refurbish these batteries.

$$W_{bdt}^{ASS-DM} = \beta_{bdt} \qquad \forall b,d,t \tag{24}$$

Constraint (24) guarantees that all of the demand points are serviced in all time periods.

$$\sum_{c} W_{bdct}^{DM-CL} = RB_{bdt} \qquad \forall b,d,t \tag{25}$$

In each time period, all retired EV batteries must be collected from the demand points. Constraint (25) provides these conditions.

$$\sum_{d} W_{bdct}^{DM-CL} = W_{bct}^{CL-ASS} + \sum_{s} W_{bcst}^{CL-SL} + \sum_{r} W_{bcrt}^{CL-RC} \qquad \forall b,c,t \tag{26}$$

$$\sum_{r} W_{bcrt}^{CL-RC} = \psi_{b}^{RC} \times \sum_{d} W_{bdct}^{DM-CL} \qquad \forall b,c,t \tag{27}$$

$$W_{bct}^{CL-ASS} = \psi_{b}^{ASS} \times \sum_{d} W_{bdct}^{DM-CL} \qquad \forall b,c,t \tag{28}$$

Constraint (26) represents the inventory balance at the collection centers. Also, the number of EV batteries shipped from the collection centers to the recycling and assembly centers are calculated by constraints (27) and (28), respectively.

$$\sum_{c} W_{bcst}^{CL-SL} = W_{bst}^{SL-I} + W_{bst}^{SL-II} \qquad \forall b,s,t \tag{29}$$

Constraint (29) states that with the retired EV batteries transferred to the second life EV battery production center, two groups of EV batteries including the type I and II second life batteries are produced.

$$W_{bst}^{SL-I} = \psi_b^{SL} \times \sum_c W_{bcst}^{CL-SL} \qquad \forall b,s,t \tag{30}$$

The number of second life EV batteries categorized in group I shipped from the second life EV battery production centers to the market are calculated by constraint (30).

$$\sum_b W_{bst}^{SL-I} \times \varphi_{qb}^3 + \sum_b W_{bst}^{SL-II} \times \varphi_{qb}^4 = \sum_g W_{qgst}^{SP-SL} \qquad \forall q,s,t \tag{31}$$

Constraint (31) shows the inventory balance at the second life EV battery production centers.

$$\sum_{b,c} W_{bcrt}^{CL-RC} \times \gamma_{pb} = \sum_f W_{prft}^{RC-DS} + \sum_g W_{prgt}^{RC-SP} \qquad \forall p,r,t \tag{32}$$

The inventory balance at the recycling centers is stated by constraint (32).

$$\sum_{b,c,e} W_{bcrt}^{CL-RC} \times \gamma_{pb} \times \Phi_{pbe} \times U_{ret}^{RC} = \sum_g W_{prgt}^{RC-SP} \qquad \forall p,r,t \tag{33}$$

Constraint (33) calculates the amount of EV battery components purchased from recycling centers by suppliers.

$$\sum_e W_{bret}^{RC} = \sum_c W_{bcrt}^{CL-RC} \qquad \forall b,r,t \tag{34}$$

The number of recycled EV batteries in each recycling center using each technology is determined by constraint (34).

$$\sum_q W_{qgt}^{SP-ASS} + \sum_{q,s} W_{qgst}^{SP-SL} \le M \times U_{gt}^{SP} \qquad \forall g,t \tag{35}$$

The condition of buying cells from each supplier is to place an order with that supplier. Constraint (35) provides this condition.

$$\sum_{b,d} W_{bdct}^{DM-CL} + \sum_b W_{bct}^{CL-ASS} + \sum_{b,s} W_{bcst}^{CL-SL} + \sum_{b,r} W_{bcrt}^{CL-RC} \le M \times U_c^{CL} \qquad \forall c,t \tag{36}$$

$$\sum_{b,c} W_{bcst}^{CL-SL} + \sum_{q,g} W_{qgst}^{SP-SL} + \sum_b W_{bst}^{SL-I} + \sum_b W_{bst}^{SL-II} \le M \times U_s^{SL} \qquad \forall s,t \tag{37}$$

Each center serves if it is established. This condition for collection and second life EV battery production centers is given in constraints (36) and (37), respectively.

$$\sum_{b,c} W_{bcrt}^{CL-RC} + \sum_{p,f} W_{prft}^{RC-DS} + \sum_{p,g} W_{prgt}^{RC-SP} \le M \times \sum_e U_{ret}^{RC} \qquad \forall r,t \tag{38}$$

$$\sum_b W_{bret}^{RC} \le M \times U_{ret}^{RC} \qquad \forall r,e,t \tag{39}$$

$$\sum_{p,r} W_{prft}^{RC-DS} \le M \times U_{ft}^{DS} \qquad \forall f,t \tag{40}$$

We can only use the recycling and disposal centers that we have ordered from. Constraints (38) and (39) provide this condition for recycling centers, and constraint (40) provides it for disposal centers.

3. Results

Table 2. The simulation algorithm for data generation.

Indices/Parameters	Functions
p,b,q,d,c,s,g,r,e,f,v,t	User should determine the value of indices
δ_{bt}^{ASS}	Uniform (35,37)
δ_{bct}^{CL}	Uniform (2,3)
δ_{bst}^{SL}	Uniform (40,45)
δ_{bret}^{RC}	Uniform (80,90)
δ_{pft}^{DS}	Uniform (5,7)
δ_{qgt}^{SP}	Uniform (40,43)
λ_{pgt}^{SP}	Uniform (6,7)
λ_{bt}^{MR-I}	Uniform (800,850)
λ_{bt}^{MR-II}	Uniform (700,750)
$\vartheta_{g}^{SP-ASS}, \vartheta_{d}^{ASS-DM}, \vartheta_{dc}^{DM-CL}, \vartheta_{c}^{CL-ASS}, \vartheta_{cs}^{CL-SL}, \vartheta_{gs}^{SP-SL}$ $\vartheta_{cr}^{CL-RC}, \vartheta_{s}^{SL}, \vartheta_{rf}^{RC-DS}, \vartheta_{rg}^{RC-SP}$	Uniform (10,20)
κ_{qgt}^{SP}	Round (Uniform (45000,60000))
κ_{c}^{CL}	Round (Uniform (1500,2000))
$\kappa_{s}^{SL}, \kappa_{re}^{RC}, \kappa_{f}^{DS}$	Round (Uniform (500,700))
κ_{v}^{VH}	Round (Uniform (3000,5000))
$\alpha_{gt}^{SP}, \alpha_{rt}^{RC}, \alpha_{ft}^{DS}$	Uniform (300,350)
$\alpha_{c}^{CL}, \alpha_{s}^{SL}$	Uniform (1000,1200)
β_{bdt}	Round (Uniform (70,90))
ξ_{vt}	Uniform (2,2.5)
WG_{b}^{1}	Uniform (100,120)
WG_{q}^{2}	Uniform (10,12)
Φ_{pbe}	Uniform (0.7,0.8)
CO_{be}^{RC}	Uniform (15,18)
CO_{v}^{VH}	Uniform (1,1.5)
γ_{pb}	Uniform (2,3)
RB_{bdt}	Round (Uniform (12,20))
$\psi_{b}^{RC}, \psi_{b}^{ASS}, \psi_{b}^{SL}$	Uniform (0.3,0.4)

In this section, we intend to examine the effectiveness of the proposed model using simulated data derived from the real world. To collect data, we used historical data and experts' knowledge of Company XYZ (The company name has been changed to protect its anonymity), which produces all kinds of lithium-ion batteries in Canada. The data collection process was associated with two challenges. First, we were not allowed to use real data directly due to privacy and competitive advantage. Second, there was no data related to some parameters in the company. The review of the literature shows that in such situations, the use of simulation tools is a solution [11]. There are various approaches to data simulation. Using probabilistic distribution functions is one of the most common ones [36,38]. Tavana et al. [11] utilized probabilistic distribution functions to simulate data in the EV battery industry. In this vein, we also apply probabilistic distribution functions to simulate data, which is displayed in Table 2.

In this paper, we utilize the LP-metric method provided by Mardan et al. [39] to convert the bi-objective MILP model to a single-objective one. In the following, the applied LP-metric method is explained briefly. In this method, we must first determine the lower (upper) bound for the minimization (maximization) objective functions. In this research, both objective functions are minimization type; therefore, we must calculate the lower bound of both objective functions. For this purpose, we optimize the proposed model for each objective function without considering the other objective function. We define Z_1^L and Z_2^L as the lower bound of the first and second objective functions, respectively. Finally, we integrate the two objective functions together using Eq 41.

$$Z^{LP} = w \times \frac{Z_1 - Z_1^L}{Z_1^L} + (1 - w) \times \frac{Z_2 - Z_2^L}{Z_2^L} \tag{41}$$

Where w shows the weight of the first objective function.

When the simulated data is used to validate the optimization models, usually several problems are simulated in different sizes and the performance of the model is examined in the simulated problems. In this regard, this article simulates the data of six problems in different sizes. The sizes of the simulated problems are presented in Table 3. Note that the size of each simulated problem has increased compared to the previous problem, which means that it has grown in at least one index.

Table 3. The size of the simulated problems.

Problem	p	b	q	d	c	s	g	r	e	f	v	t
P1	1	1	1	3	2	2	2	2	2	2	1	2
P2	2	1	2	4	2	2	2	2	2	2	2	2
P3	3	2	2	4	3	2	3	2	2	2	2	3
P4	3	2	3	5	3	3	3	3	3	3	3	3
P5	3	3	3	6	3	3	4	3	3	3	3	4
P6	4	3	3	7	3	3	4	3	3	3	3	4

Now we intend to implement the proposed model for simulation problems in GAMS software. For this purpose, we must first change the bi-objective model to a single-objective one by applying the LP-metric method shown in Eq 41. Before applying the LP-metric method, we calculate the lower bound of the objective functions, which are given in Table 4.

Table 4. The lower bound and optimal values of the objective functions.

Problem	Z_1^L	Z_2^L
P1	213916	848.68
P2	279448	2194.58
P3	814667	7040.87
P4	1005299	10500.74

P5	2502051	26525.48
P6	2814997	25935.58

Then, with the help of Eq 41, the objective function related to the LP-metric method is structured for each simulated problem, which is reported in Table 5. It should be noted that the value of *w* is 0.6.

Table 5. The LP-metric objective function for each problem.

Problem	Z^{LP}
P1	$0.6\times\frac{Z_1-213916}{213916}+0.4\times\frac{Z_2-848.68}{848.68}$
P2	$0.6\times\frac{Z_1-279448}{279448}+0.4\times\frac{Z_2-2194.58}{2194.58}$
P3	$0.6\times\frac{Z_1-814667}{814667}+0.4\times\frac{Z_2-7040.87}{7040.87}$
P4	$0.6\times\frac{Z_1-1005299}{1005299}+0.4\times\frac{Z_2-10500.74}{10500.74}$
P5	$0.6\times\frac{Z_1-2502051}{2502051}+0.4\times\frac{Z_2-26525.48}{26525.48}$
P6	$0.6\times\frac{Z_1-2814997}{2814997}+0.4\times\frac{Z_2-25935.58}{25935.58}$

We ran the proposed model using simulated data in GAMS software and employed the CPLEX solver for this purpose. The optimal values of the objective functions for each simulated problem are denoted in Table 6. In addition, the runtime of the model in GAMS software for each problem is reported in Table 6. The results make it clear that the runtime grows as the problem size increases.

Table 6. The optimal values of objective functions for each problem.

Problem	First objective function	Second objective function	Runtime (second)
P1	214969	848.68	43.71
P2	279918	2194.58	188.06
P3	821917	7073.52	386.92
P4	1016309	10581.32	867.55
P5	2525691	27420.06	1278.23
P6	2860242	26514.57	1834.89

By comparing the results reflected in Tables 4 and 6, the logical performance of the model and the correctness of the results obtained from it are confirmed. The values presented in Table 4 are the lower bound of the objective functions and since both objective functions are minimization, the optimal value calculated for the objective functions by the LP-metric method should not be smaller than their lower bound. For example, the lower bound of the first and second objective functions for the first problem are equal to 213916 and 848.68, respectively. According to logical expectations, the optimal value obtained for both objective functions using the LP-metric method should be greater than or equal to their lower bound. In Table 6, the optimal values of the first and second objective functions for the first problem are 214969 and 848.68, respectively, which indicates the accuracy of the results obtained from the model.

4. Sensitivity analysis

In this section, the correctness of the performance of the proposed model is investigated by performing the sensitivity analysis process. For this purpose, the sensitivity analysis process will be implemented on the demand and objective functions coefficients. In the following, first, the results of the demand sensitivity analysis are presented. Then the results obtained from the sensitivity analysis of the objective function coefficients are reported.

4.1. Sensitivity analysis of demand

In this section, we implement the sensitivity analysis process on the demand parameter (i.e., β_{bdt}). Note that problem 4 (i.e., P4) is used for this purpose. We expect that with the increase in demand, the values of the first and second objective functions will not improve, and with its decrease, the values of both objective functions will not worsen. In this vein, we defined nine scenarios based on changes in the demand values of problem 4 and ran the proposed model for all scenarios in GAMS software. It should be noted that scenario 5 is the same as problem 4, and by moving from scenario 5 to scenario 1, the demand will gradually decrease. By moving from scenario 5 to scenario 9, the demand will gradually increase. The mentioned scenarios along with their results are given in Table 7. Also, the behavior of the first and second objective functions for moving from scenario 1 to scenario 9 is shown in Figures 2 and 3, respectively.

Table 7. The results obtained from the demand sensitivity analysis.

Scenario	Demand	Objective function 1	Objective function 2
S1-1	$0.8\times\beta_{bdt}$	842390	9521.08
S1-2	$0.85\times\beta_{bdt}$	931544	9752.63
S1-3	$0.9\times\beta_{bdt}$	961912	10016.45
S1-4	$0.95\times\beta_{bdt}$	983674	10276.11
S1-5 (P4)	β_{bdt}	1016309	10581.32
S1-6	$1.05\times\beta_{bdt}$	1053642	10903.50
S1-7	$1.1\times\beta_{bdt}$	1089117	11233.98
S1-8	$1.15\times\beta_{bdt}$	1178738	11496.72
S1-9	$1.2\times\beta_{bdt}$	1210043	11764.62

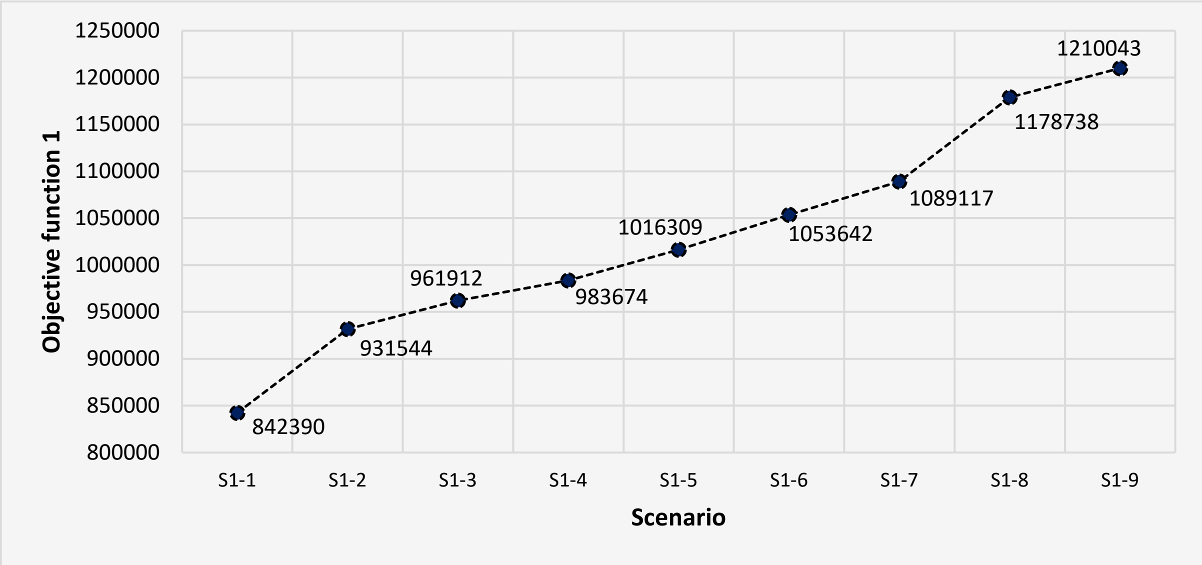

Figure 2. The behavior of objective function 1 for moving from scenario 1 to scenario 9.

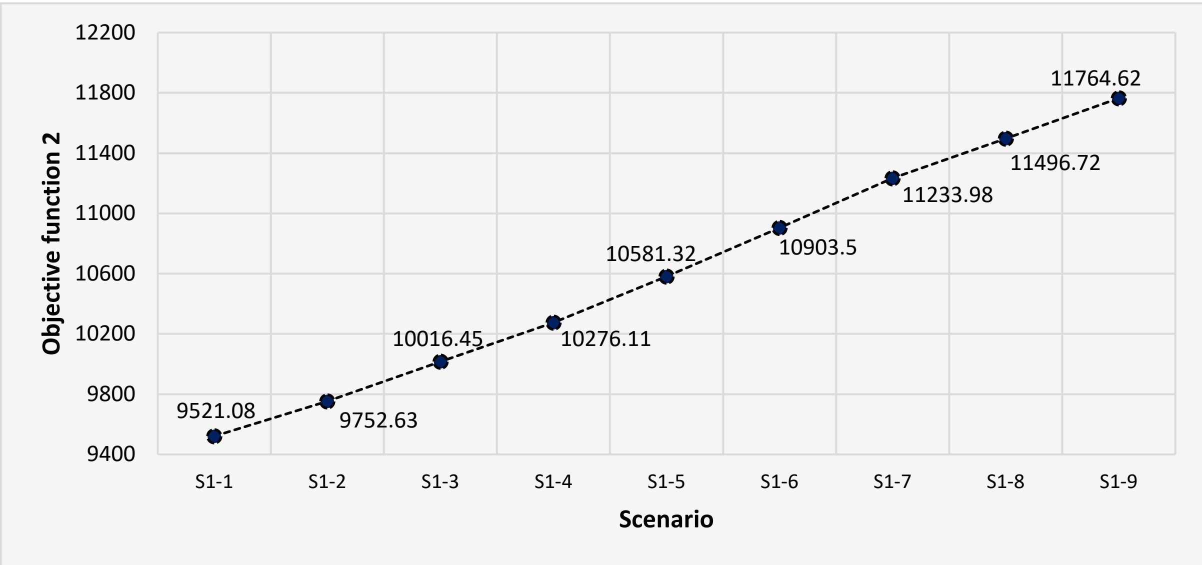

Figure 3. The behavior of objective function 2 for moving from scenario 1 to scenario 9.

The results reported in Table 7 show that with the increase (decrease) in demand, the value of both objective functions increase (decrease), which is in line with reasonable expectations.

4.2. Sensitivity analysis of objective function coefficients

In this section, the sensitivity of the proposed model to the objective functions coefficients is investigated. Similarly, the sensitivity analysis process is implemented on problem 4. When the coefficient of one objective function increases, the coefficient of the other objective function will certainly decrease. Therefore, it is expected that the optimal value of the objective function whose coefficient is increased will not worsen. On the other hand, we expect that the optimal value of the objective function whose coefficient is reduced will not improve. In Table 8, we have defined seven scenarios with changes in the coefficients of the objective functions. The results of each scenario are given in Table 8. Also, the behavior of the first and second objective functions for moving from scenario 1 to scenario 7 is denoted in Figures 4 and 5, respectively.

Table 8. The results obtained from the sensitivity analysis of the objective functions coefficients.

Scenario	*w*	1-*w*	Objective function 1	Objective function 2
S2-1	0.4	0.6	1027885	10522.44
S2-2	0.45	0.55	1023559	10539.16
S2-3	0.5	0.5	1021678	10554.70
S2-4	0.55	0.45	1018950	10572.63
S2-5 (P4)	0.6	0.4	1016309	10581.32
S2-6	0.65	0.35	1013682	10589.21
S2-7	0.7	0.3	1011203	10596.94

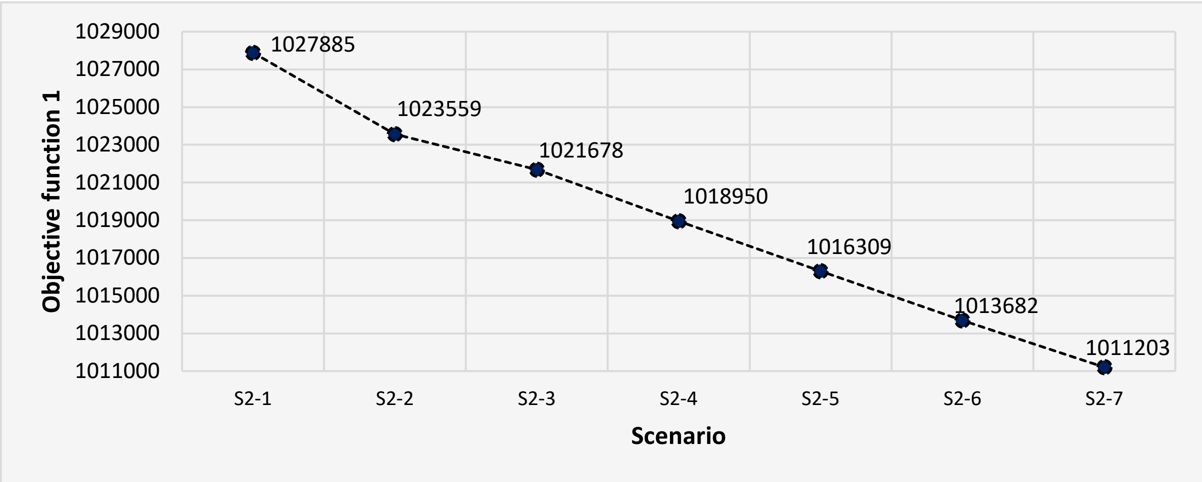

Figure 4. The behavior of objective function 1 for moving from scenario 1 to scenario 7.

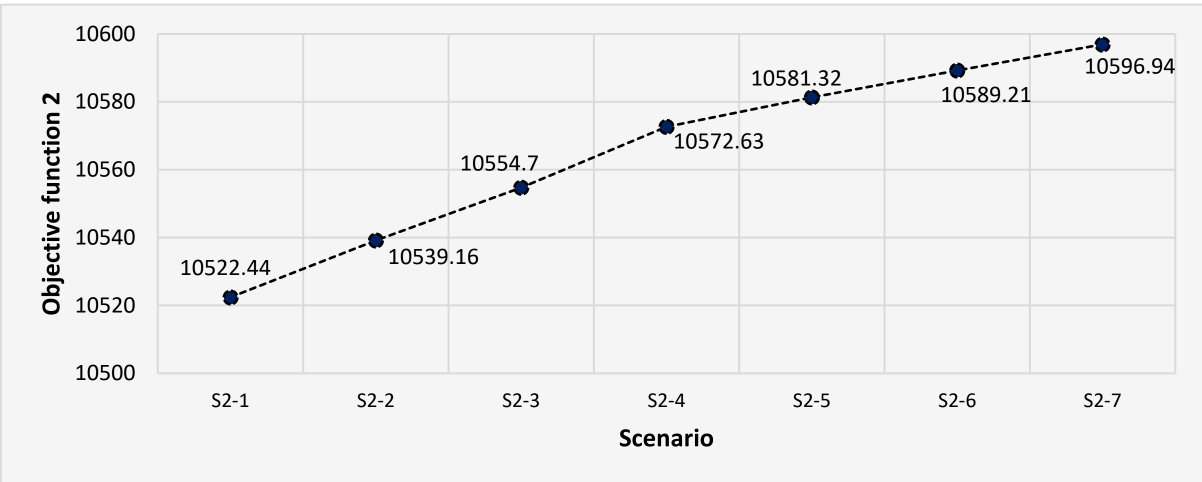

Figure 5. The behavior of objective function 2 for moving from scenario 1 to scenario 7.

The results of Table 8 show that when the coefficient of each objective function increases, its optimal value decreases. Conversely, by decreasing the coefficient of each objective function, its optimal value increases. This means that the performance of the model is in line with reasonable expectations. Therefore, it can be concluded that the proposed model performs well and the results obtained from it are reliable.

5. Managerial implications

The current model aims at providing the conditions for the establishment of a circular supply chain network through which cost minimization, reduction of CO2 emission, resource use optimization, and sustainability improvement will come into play. This model enjoys the potential to act as an effective tool for stakeholders' decision-making where they can detect the intricacies of the EV battery supply chain. In this way, sustainability practices are valued more than ever and, thereby, a bright resource-efficient future will be there.

Moreover, manufacturers and decision-makers in this supply chain can benefit from this presented model, especially in terms of the EV battery issues. Manufacturers can make the best possible decisions so that collection centers will be set up effectively, optimal transportation requirements can be determined, and suitable suppliers will be selected optimally. When valuing the lifespan of EV batteries, the manufacturers will be able to set a sustainable supply chain network with the aim of mitigating costs and environmental adverse effects as well as improving resource efficiency.

When it comes to operational decision-making, the optimization model helps practitioners and policymakers to deal with the issues of second-life EV battery production, recycling, and disposal. It is of help to decision-makers to determine the best possible recycling technologies, optimize item flow among various echelons, and opt for effective resource use. Such operational decisions improve the sustainable and circular nature of the EV battery supply chain.

The production and distribution affairs of manufacturers can be optimally improved by means of this model. When the element of circularity is integrated into the supply chain network, manufacturers will be able to minimize their costs pertaining to the procurement and disposal of raw materials and also minimize CO2 emissions. This leads to both the betterment of environmental function and increased competitiveness and good image as sustainable manufacturers.

Manufacturers involved in recycling have a critical role in the circular supply chain with regard to EV batteries where the optimization model greatly helps with the decision-making processes. In this regard, they can make educated decisions in terms of collection, sorting, and recycling processes. When recyclers optimize the selection of recycling affairs and go for the optimal flow of materials, they can minimize waste production and negative environmental impacts. By using this model, recyclers will have the ability to put sustainability into practice with regard to EV battery materials.

Note that consumers as a part of the supply chain network are effective in the development of circular networks in the EV battery industry. Increasing environmental awareness of consumers can be a strong incentive to use refurbished batteries instead of new batteries. The cost-effectiveness of refurbished batteries compared to new batteries is another factor that is definitely important for consumers. Some consumers may refuse to use these batteries due to a lack of knowledge about the quality and lifespan of refurbished batteries. It is undeniable that a large part of increasing consumer awareness depends on the policies adopted by governments.

It should be noted that policymakers play a key role in improving the performance of supply chain networks. Their decisions can have a direct impact on increasing network efficiency, and reducing costs and emissions. Therefore, in this research, we suggest the following policy recommendations to improve network performance:

- It is suggested that policymakers focus on cooperation between battery recyclers and electric vehicle manufacturers. By promoting cooperation and partnerships, there can be a more efficient flow of resources, information, and expertise, leading to improved sustainability and circularity in the EV battery industry.
- It is suggested that governments and policymakers take policies based on financial incentives, such as granting long-term and low-interest facilities, tax exemptions, etc., to lead manufacturers and recyclers of EV batteries to adopt sustainable practices.
- Policymakers should establish strict regulations for proper recycling and disposal of EV batteries. By applying proper disposal and responsible recycling practices, the harmful effects on the environment can be significantly reduced.
- Governments should prioritize public awareness educational programs for promoting the importance of sustainable practices in the EV battery supply chain. Consumers can support sustainable initiatives and make informed choices by increasing public understanding of the social and environmental impacts of EV batteries and the benefits of circularity.

6. Conclusion

Recently, researchers have used the concept of a circular economy to increase the sustainability of supply chain networks. Applying the circular economy concept in the EV battery production industry has a significant effect on increasing the lifespan of battery components, reducing the use of resources, reducing costs, and generally increasing the sustainability of the supply chain network. Therefore, in this study, a new bi-objective MILP model was formulated for the structuring of a comprehensive supply chain network in the EV battery production industry considering the circular economy concept. Inspired by real-world assumptions, the proposed model optimized both strategic and operational decisions, and its objectives were to minimize total costs and CO2 emissions simultaneously. In the investigated network, retired batteries are divided into three categories: (1) refurbishable batteries used in EVs, (2) refurbishable batteries applied in other industries, and (3) batteries whose components must be recycled. In the proposed network, several heterogeneous recycling technologies are considered for the processing of unusable batteries, which differ from each other in terms of efficiency, processing cost, and CO2 emission. It should be noted that we applied the LP-metric method to create a balance between total costs and CO2 emissions, and used the scaled data of an EV battery manufacturing company in Canada to validate our proposed model. The results obtained from running the model for the simulated problems revealed that the proposed model had good performance and its outputs were reliable.

Every research has its own set of weaknesses and strengths. Researchers should acknowledge and address these limitations in order to identify potential avenues for future research. In the following, we will discuss the limitations of the current paper and present suggestions for future studies:

- In this paper, we presented our proposed model without considering regulatory approaches and geographical differences. In different regions, there are various regulations on recycling processes, disposal, and emission standards, which significantly affect the model results. It is suggested to consider regional regulations in the structuring of the model in future researches and examine how much this criterion affects the results.

- The model presented in this research is not resilient and external shocks, such as a lack of raw materials, fluctuations in demand, etc., can lead to network disruption. It is suggested to design a resilient supply chain network in the EV battery industry by using resilience strategies, such as cooperation with third-party logistics, collaboration with backup suppliers, etc., in future research.
- The EV battery industry is a dynamic and evolving industry. The technologies applied in this industry, especially recycling technologies, are changing rapidly. Although our model considers multiple recycling technologies, its dynamics and consequences are not considered in the network design. It is suggested to develop a dynamic model in the field of EV battery management by focusing on the challenges associated with emerging technologies and considering the speed of development of these technologies.
- In every industry, the transition from a traditional supply chain to a circular supply chain is associated with barriers and challenges. The EV battery industry is no exception to this. In this research, we have not considered the barriers of circular economy implementation in the network design. While there are many challenges to integrate new practices related to a circular economy with existing logistics and production processes. It is suggested that, in future studies, the barriers to the implementation of a circular economy in the EV battery industry should be identified and strategies to deal with them should be provided. In addition, it is suggested to consider some of these barriers, such as the high cost of setup, infrastructural limitations, etc., in the network design, and investigate the long-term effects of the transition from the traditional supply chain to the circular supply chain in reducing costs and CO2 emissions.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

Conflict of interest

The authors declare that there are no conflicts of interest in this paper.

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