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A sustainable circular supply chain network design model for electric vehicle battery production using internet of things and big data

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Abstract

Designing and developing sustainable circular supply chain networks for electric vehicle (EV) lithium-ion battery recycling and production requires complex environmental sustainability and economic viability assessment. EVs use a lot of data for battery management and delivering optimum performance, and the Internet of Things (IoT) plays a major role in managing this data. This study develops a bi-objective mixed-integer linear programming model for designing a sustainable circular supply chain to manage the manufacturing, remanufacturing, and distribution of EV lithium-ion batteries under uncertainty using the IoT and big data. The proposed model simultaneously minimizes total costs and CO_2 emissions and uses IoT to improve network performance and create a traceable and secure environment. A fuzzy multi-objective method solves the bi-objective optimization model under uncertainty, and a simulation algorithm examines the effectiveness of the proposed model through simulated problems.

KEYWORDS
big data, electric vehicle, internet of things, lithium-ion battery, sustainable circular supply chain, uncertainty

1 | INTRODUCTION

Circular economy (CE) is a concept that has recently emanated from decreasing the use of inputs when focused on industrial production (Kirchherr et al., 2017; Stahel, 2016). The increasing popularity of the CE model dates back to the late 1970s when it is difficult to reach a consensus on a single definition for CE due to its non-stop development and multidisciplinary status (Tushar et al., 2022). In this regard, two factors centred upon CE are its multi-phased employment of energy and raw materials and its closed or circular flow of materials (Franklin-Johnson et al., 2016; Tomić & Schneider, 2018). In other words, CE can be referred to as an economy that aims to decrease the use of materials, use of energy, and environmental pollution while economic development is not adversely affected (Benachio et al., 2020; Castro et al., 2022). Although CE is concerned about sustainability, major differences exist between CE and sustainability regarding goals, institutionalization process, origins, responsibility perception, and motivations (Geissdoerfer et al., 2017).

When it comes to CE, one can easily refer to the "3 Rs" principle, which refers to "reduce," "reuse," and "recycle" the materials to minimize the unessential inputs and the leakages (Tushar et al., 2022). Various approaches are used in a CE to obtain this objective. One can refer to the design of products with multiple uses, the increase of product life cycles toward increased utilization, the reuse of wastes, and so forth (Gupta et al., 2022; Genc, 2021). CE models have become popular with policymakers, and several countries are adopting new rules and policies to develop these models. For instance, it is possible to name the "Closed Substance Cycle and Waste Management Act" in Germany, "Basic Law for Establishing a Recycling-Based Society" in Japan, and "CE Promotion Law of the People's Republic of China" in China (Lieder & Rashid, 2016; Su et al., 2013).

The Electric Vehicle (EV) lithium-ion batteries industry is one industry in which CE can significantly help reduce costs and destructive environmental effects (Yu et al., 2021). The past decade witnessed the vast development of electric vehicles, where their global stock also experienced a 63% increase in 2017 (Hua et al., 2021). This figure reached 5 million in 2018. It has been estimated that these devices can cover from 11% to 28% of road transport needs worldwide by 2040 (Kapustin & Grushevenko, 2020). Because of their great power density and energy, low self-discharge rate, high reliability, and long lifespan, spent lithium-ion batteries are largely used in such devices (Wen et al., 2020; Zhang et al., 2022). They can travel 120,000 to 240,000-km distance during their lifetime, and these batteries can have an 8- to 10-year-old lifespan (Ansari et al., 2021; Martinez-Laserna et al., 2018). Notably, the wasted batteries of the 5 million electric vehicles will have a total weight of 1.25 million tons at the end of the vehicles' lifetime because each battery weighs about 250 kg (Hua et al., 2021). Remanufacturing spent lithium-ion batteries through the wasted batteries is being regarded as a desirable end-of-life option for the batteries of electric vehicles as they can potentially decrease the environmental pollution arising from waste disposal and battery production (Xiong et al., 2020). In addition, remanufacturing these batteries using spent batteries can control possible illogical price increases and prevent the disruption of battery materials supply, especially because the supply of these materials is greatly dependent on the import of cobalt and nickel from other countries (Rallo et al., 2020).

This paper develops a novel bi-objective mixed-integer linear programming model (MILP) to structure a sustainable circular supply chain (SCSC) network for managing EV lithium-ion batteries under uncertainty and a big data environment. It should be emphasized that the Internet of Things (IoT) technology will be applied to increase transparency in the network, prevent fraud, and make the batteries traceable. The presented model aims to minimize total network costs and CO_2 emissions simultaneously. In general, the contributions of this research can be expressed as follows:

- Formulating a novel MILP model to design a virtual SCSC network for managing the spent EV lithium-ion batteries;
- Applying a fuzzy multi-objective solution method for solving the presented bi-objective optimization model;
- Developing a data simulation approach with feasible solution spaces based on three dimensions of big data (i.e., volume, variety, and velocity);
- Validating the presented model and solution approach using 10 simulated test problems in different sizes.

The remainder of this paper is organized as follows. The relevant literature is investigated in Section 2. The proposed model and the multi-objective solution method are presented in Sections 3 and 4, respectively. Sections 5 and 6 are devoted to case study and sensitivity analysis. Comparative analysis and discussion are presented in Sections 7 and 8. Finally, the conclusion is presented in Section 9.

2 | LITERATURE REVIEW

A mathematical planning tool is a practical tool in supply chain network design. Literature review shows that mathematical models have been used abundantly in the structuring of traditional supply chains (Farahani et al., 2014; Govindan et al., 2017; Hu et al., 2023), green/sustainable supply chains (Ebrahim Qazvini et al., 2021; Joshi, 2022; Nasiri et al., 2023), closed-loop/circular supply chains (Govindan et al., 2020; Govindan et al., 2023; Zhang et al., 2021), sustainable closed-loop/circular supply chains (Tavana et al., 2022; Zhang et al., 2023; Zhen et al., 2019), and virtual supply chains (Prajapati, Chan, et al., 2022 and 2002b; Shambayati et al., 2022).

To design a green Closed-Loop Supply Chain (CLSC) network including reverse and forward flows, Mardan et al. (2019) suggested a bi-objective MILP model and a benders decomposition algorithm to optimize operational and strategic decisions in the cable and wire industry. The objective functions of their model are dedicated to economic and environmental issues and simultaneously minimize the negative environmental effects and the total costs. Hajiaghaei-Keshteli and Fathollahi Fard (2019) developed a sustainable CLSC network considering discounts via a mixed-integer non-linear programming (MINLP) model. They considered all three sides of sustainability (i.e., social, environmental, and economic) in structuring the investigated network. They evaluated the efficiency of their proposed model using data from the glass industry. Nasr et al. (2021) presented a hybrid framework based on a MILP model and multi-criteria decision-making techniques for structuring a sustainable CLSC network considering circular supplier evaluation under uncertainty. They employed a fuzzy goal programming (GP) approach for solving their presented multi-objective optimization model and used data from the garment industry to validate it. Using resilience and sustainability strategies, Mehrjerdi and Shafiee (2021) configured a CLSC network to reduce network risks and increase economic, environmental, and social efficiency. Their model minimizes environmental effects and total costs and maximizes job creation. They applied an augmented epsilon-constraint method for solving their multi-objective optimization model.

Soleimani et al. (2022) developed a heuristic algorithm to solve a CLSC problem considering energy consumption and sustainability. They minimize energy consumption and costs and maximize job opportunities with the help of a multi-objective MILP model. Seydanlou et al. (2022) designed a sustainable CLSC network to optimize strategic and operational decisions in the olive industry. They used meta-heuristic algorithms to solve their proposed problem. Govindan et al. (2022) presented a bi-objective optimization model for healthcare waste management to transition toward CE. They employed a stochastic scenario-based method to control uncertain parameters and an augmented epsilon-constraint method for solving their presented bi-objective optimization model. Tavana et al. (2022) formulated a comprehensive model to form a sustainable CLSC network by focusing on all three aspects of sustainability. In their model, the economic objective function minimizes total costs, the environmental objective function minimizes CO_2 emissions, and the social objective function maximizes job opportunities. They employed a fuzzy GP method to solve their multi-objective MILP model.

Shambayati et al. (2022) proposed a virtual CLSC network for the first time using the concept of IoT and mathematical programming tools. The aim of their model was profit maximization, and they utilized meta-heuristic algorithms to solve their problem. In this vein, Prajapati, Jauhar, et al. (2022) structured a virtual CLSC network using an MINLP model. They used IoT devices and blockchain technology for this purpose. In addition, Tavana et al. (2023) formulated an optimization model for configuring an SCSC network and developed a Lagrangian relaxation algorithm to solve problems of large sizes. They applied an artificial IoT to increase the security and performance of the network and create a traceable environment. A MILP model to optimize a CLSC in the agricultural industry to minimize strategic and operational costs was developed by Rajabi-Kafshgar et al. (2023). They used meta-heuristic algorithms to solve their presented problem. Govindan et al. (2023) proposed a circular CLSC network for structuring an inventory-location-routing problem considering a carbon tax policy in the cable and wire industry. Their MILP model minimizes total costs and lost sales simultaneously. They applied an augmented epsilon-constraint method to solve their presented bi-objective optimization model. Goodarzian et al. (2023) structured a sustainable circular CLSC network with the help of a multi-objective MILP model to increase sustainability in the citrus industry. They utilized the epsilon-constraint method for solving their tri-objective model and developed meta-heuristic algorithms to solve their problem in large sizes. A bi-objective MINLP model for designing a CLSC network in the mobile phone industry was formulated by Keshavarz-Ghorbani and Pasandideh (2023) to optimize strategic and operational decisions. Their model aims to create a trade-off between social benefit and profit. They used an epsilon-constraint method to solve their bi-objective model.

Table 1 shows the similarities and differences between the papers presented in the CLSC/reverse supply chain network area and the current paper to reveal the research gap. As seen in Table 1, so far, no research has focused on designing a CLSC/reverse supply chain network to optimize EV lithium-ion batteries considering IoT technology in the big data environment. For this purpose, based on our best knowledge, in this research, for the first time, a novel bi-objective MILP model for structuring a CLSC network to manage the production, distribution, and recycling of EV lithium-ion batteries by considering the concepts of CE, IoT technology, capacity level, inventory management, facility location, and big data are developed under uncertainty.

3 | PROPOSED MODEL

This section proposes a novel bi-objective MILP model to design a sustainable circular CLSC network to manage the manufacturing, remanufacturing, and distribution of EV lithium-ion batteries. In the investigated network, the manufacturing centre transfers the batteries to the distribution centres so that the distribution centres distribute the batteries between battery swap stations. At the battery swap station, spent batteries are identified and delivered to collection centres. Then, the defective batteries are sent to the manufacturing centre. Defective batteries are remanufactured in the manufacturing centre and enter the consumption cycle again. The investigated network is depicted in Figure 1. It should be noted that the investigated CLSC network is configured based on the structure and activities of a large company that produces EV lithium-ion batteries in the Middle East. Therefore, the assumptions considered for formulating the proposed model are real and taken from the studied network structure. These assumptions are given below:

- The investigated network is multi-period and multi-product and includes both forward and reverse flows.
- One manufacturing centre is considered.
- Vehicles and centres are capacitated.
- The capacity level has been defined for collection and distribution centres.
- The model locates distribution and collection centres.
- Storage in distribution centres is allowed.
- IoT technology is used to create a traceable and safe environment.

TABLE 1 Papers investigated the reverse supply chain area to reveal the research gap.

	Multi-period	Multi-product	Multi-objective	Facility location	Storage	Capacity level	Forward flow	Reverse flow	CLSC	CE	Environmental issues	Big data	IoT technology	EV lithium-ion batteries	Uncertainty
Mardan et al. (2019)	√	√	√	√	√	-	√	√	√	-	√	-	-	-	-
Hajiaghaei-Keshteli and Fathollahi Fard (2019)	-	-	√	√	-	-	√	√	√	-	√	-	-	-	-
Nasr et al. (2021)	√	√	√	√	√	-	√	√	√	√	√	-	-	-	√
Mehrjerdi and Shafiee (2021)	-	√	√	√	√	-	√	√	√	-	√	-	-	-	√
Soleimani et al. (2022)	√	√	√	√	√	-	√	√	√	-	√	-	-	-	-
Govindan et al. (2022)	√	√	√	√	-	-	-	√	-	√	√	-	-	-	√
Tavana et al. (2022)	√	√	√	√	√	-	√	√	√	√	√	-	-	-	√
Shambayati et al. (2022)	√	√	-	√	√	-	√	√	√	-	-	-	√	-	√
Prajapati, Jauhar, et al. (2022)	√	√	√	-	√	-	√	√	√	√	√	-	√	-	-
Tavana et al. (2023)	√	√	-	√	√	√	√	√	√	√	√	-	√	-	-
Govindan et al. (2023)	√	√	√	√	√	-	√	√	√	√	√	-	-	-	√
Goodarzian et al. (2023)	√	-	√	√	√	-	√	√	√	√	√	-	-	-	-
Keshavarz-Ghorbani and Pasandideh (2023)	√	√	√	√	√	-	√	√	√	-	√	-	-	-	-
This Study	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√

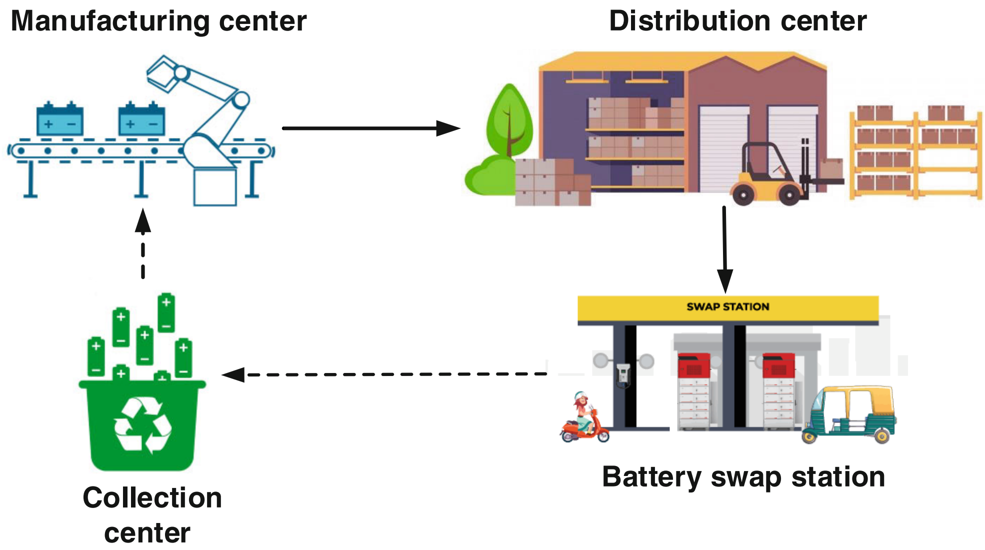

FIGURE 1 The investigated supply chain network for EV lithium-ion batteries.

3.1 | Mathematical model

3.1.1 | Indices

b/B	Index/set of batteries	$b \in \{1,2,...,B\}$
d/D	Index/set of distribution centres	$d \in \{1,2,...,D\}$
c/C	Index/set of collection centres	$c \in \{1,2,...,C\}$
k/K	Index/set of capacity levels for distribution centres	$k \in \{1,2,...,K\}$
k'/K'	Index/set of capacity levels for collection centres	$k' \in \{1,2,...,K'\}$
s/S	Index/set of battery swap stations	$s \in \{1,2,...,S\}$
v/V	Index/set of vehicles	$v \in \{1,2,...,V\}$
i/I	Index/set of IoT technologies	$i \in \{1,2,...,I\}$
t/T	Index/set of periods	$t \in \{1,2,...,T\}$

3.1.2 | Parameters

MN_{bt}^{CST}	The cost of manufacturing one unit of type b battery at the manufacturing centre in period t
RMN_{bt}^{CST}	The cost of remanufacturing one unit of type b battery at the manufacturing centre in period t
PDC_{bdt}^{CST}	The cost of processing a unit of type b battery at distribution centre d in period t
HDC_{bdt}^{CST}	The cost of holding one unit of type b battery at distribution centre d in period t
SDC_{dk}^{CST}	The cost of establishing the distribution centre d with capacity level k
LDC_{k}^{CP}	The lower bound of capacity level k for distribution centres
UDC_{k}^{CP}	The upper bound of capacity level k for distribution centres
DBS_{bst}	The demand for battery swap station s for type b battery in period t
RBS_{bst}	Number of unusable type b battery transferred to collection centres by battery swap station s in period t
PCC_{bct}^{CST}	The cost of processing one unit of type b battery at collection centre c in period t

(Continues)

$SCC_{ck'}^{CST}$	The cost of establishing the collection centre *c* with a capacity level k'
$LCC_{k'}^{CP}$	The lower bound of capacity level k' for collection centres
$UCC_{k'}^{CP}$	The upper bound of capacity level k' for collection centres
IoT_{i}^{MN}	The cost of installing the type *i* IoT technology at the manufacturing centre
IoT_{id}^{DC}	The cost of installing the type *i* IoT technology at the distribution centre *d*
IoT_{ic}^{CC}	The cost of installing the type *i* IoT technology at the collection centre *c*
TG_t	The cost of purchasing one unit of RFID tags in period *t*
IoT_{i}^{EN}	The amount of energy required to record, process, and send data of each battery by type *i* IoT technology
PEN	Price per unit of energy consumed by IoT technologies
DIS_{d}^{MD}	The distance between the manufacturing centre and the distribution centre *d*
DIS_{ds}^{DB}	The distance between the distribution centre *d* and the battery swap station *s*
DIS_{sc}^{BC}	The distance between the battery swap station *s* and the collection centre *c*
DIS_{c}^{CM}	The distance between the collection centre *c* and the manufacturing centre
RVH_v	Transportation cost per unit of distance by vehicle *v*
$CPVH_v$	The capacity of vehicle *v*
$COVH_v$	The amount of CO_2 emitted per unit of distance by the vehicle *v*
$COIoT$	The amount of CO_2 emitted per unit of energy consumption
α_b	The volume of type *b* battery
β_b	Weight of type *b* battery
M	A large number

3.1.3 | Variables

θ_{dk}^{DC}	Binary variable; 1 if distribution centre *d* is established with the capacity level *k*, 0 otherwise
$\theta_{ck'}^{CC}$	Binary variable; 1 if collection centre *k* is established with the capacity level k', 0 otherwise
δ_{i}^{MN}	Binary variable; 1 if type *i* IoT technology is installed at the manufacturing centre, 0 otherwise
δ_{id}^{DC}	Binary variable; 1 if type *i* IoT technology is installed at the distribution centre *d*, 0 otherwise
δ_{ic}^{CC}	Binary variable; 1 if type *i* IoT technology is installed at the collection centre *c*, 0 otherwise
μ_{bt}	Integer variable; Number of the type *b* battery manufactured at the manufacturing centre in period *t*
X_{bdt}^{MD}	Integer variable; Number of the type *b* battery transferred from the manufacturing centre to the distribution centre *d* in period *t*
X_{bdst}^{DB}	Integer variable; Number of the type *b* battery transferred from the distribution centre *d* to the battery swap station *s* in period *t*
X_{bsct}^{BC}	Integer variable; Number of the type *b* battery transferred from the battery swap station *s* to the collection centre *c* in period *t*
X_{bct}^{CM}	Integer variable; Number of the type *b* battery transferred from the collection centre *c* to the manufacturing centre in period *t*
λ_{bdt}	Integer variable; Inventor level for type *b* battery at the warehouse of distribution centre *d* in period *t*
Y_{vdt}^{MD}	Integer variable; Number of the type *v* vehicle required to transfer batteries from the manufacturing centre to the distribution centre *d* in period *t*
Y_{vdst}^{DB}	Integer variable; Number of the type *v* vehicle required to transfer batteries from the distribution centre *d* to the battery swap station *s* in period *t*
Y_{vsct}^{BC}	Integer variable; Number of the type *v* vehicle required to transfer batteries from the battery swap station *s* to the collection centre *c* in period *t*
Y_{vct}^{CM}	Integer variable; Number of the type *v* vehicle required to transfer batteries from the collection centre *c* to the manufacturing centre in period *t*

3.2 | Objective functions

$$\begin{aligned}
MinZ_1 = & \sum_{b,t} MN_{bt}^{CST} \times \mu_{bt} + \sum_{b,c,t} RMN_{bt}^{CST} \times X_{bct}^{CM} + \sum_{b,d,t} PDC_{bdt}^{CST} \times X_{bdt}^{MD} + \\
& \sum_{b,d,t} HDC_{bdt}^{CST} \times \lambda_{bdt} + \sum_{d,k} SDC_{dk}^{CST} \times \theta_{dk}^{DC} + \sum_{b,s,c,t} PCC_{bct}^{CST} \times X_{bsct}^{BC} + \sum_{c,k'} SCC_{ck'}^{CST} \times \theta_{ck'}^{CC} + \\
& \sum_{i} IoT_i^{MN} \times \delta_i^{MN} + \sum_{i,d} IoT_{id}^{DC} \times \delta_{id}^{DC} + \sum_{i,c} IoT_{ic}^{CC} \times \delta_{ic}^{CC} + \sum_{b,t} TG_t \times \mu_{bt} + \\
& \sum_{i} PEN \times IoT_i^{EN} \times \left(\sum_{b,d,t} X_{bdt}^{MD} + \sum_{b,d,s,t} X_{bdst}^{DB} + \sum_{b,s,c,t} X_{bsct}^{BC} + \sum_{b,c,t} X_{bct}^{CM} \right) + \\
& \sum_{v,d,t} RVH_v \times DIS_d^{MD} \times Y_{vdt}^{MD} + \sum_{v,d,s,t} RVH_v \times DIS_{ds}^{DB} \times Y_{vdst}^{DB} + \\
& \sum_{v,s,c,t} RVH_v \times DIS_{sc}^{BC} \times Y_{vsct}^{BC} + \sum_{v,c,t} RVH_v \times DIS_c^{CM} \times Y_{vct}^{CM}
\end{aligned} \tag{1}$$

The first objective function deals with the minimization of total network costs. These costs include the costs of manufacturing and remanufacturing the batteries in the manufacturing centre, the cost of processing the batteries in the distribution centres, the cost of holding the batteries at the warehouses of the distribution centres, the cost of establishing the distribution centres with the variable capacity levels, the cost of processing the defective batteries at the collection centres, the cost of establishing the collection centres with the variable capacity, the cost of installing the IoT technology at the manufacturing, distribution, and collection centres, the cost of purchasing the RFID tags, the cost of energy consumption by IoT technology, and the cost of transporting the batteries between echelons.

$$\begin{aligned}
MinZ_2 = & \sum_{i} COIoT \times IoT_i^{EN} \times \left(\sum_{b,d,t} X_{bdt}^{MD} + \sum_{b,d,s,t} X_{bdst}^{DB} + \sum_{b,s,c,t} X_{bsct}^{BC} + \sum_{b,c,t} X_{bct}^{CM} \right) + \\
& \sum_{v,d,t} COVH_v \times DIS_d^{MD} \times Y_{vdt}^{MD} + \sum_{v,d,s,t} COVH_v \times DIS_{ds}^{DB} \times Y_{vdst}^{DB} + \\
& \sum_{v,s,c,t} COVH_v \times DIS_{sc}^{BC} \times Y_{vsct}^{BC} + \sum_{v,s,c,t} COVH_v \times DIS_c^{CM} \times Y_{vct}^{CM}
\end{aligned} \tag{2}$$

The second objective function deals with the minimization of CO_2 emissions resulting from energy consumption by IoT technology and transportation.

s.t.

$$\frac{\sum_b X_{bdt}^{MD} \times \beta_b}{CPVH_v} \leq Y_{vdt}^{MD} \leq \frac{\sum_b X_{bdt}^{MD} \times \beta_b}{CPVH_v} + 1 \ \forall v,d,t \tag{3}$$

The number of the type v vehicle required to transfer batteries from the manufacturing centre to the distribution centres in each period is calculated by constraint (3).

$$\frac{\sum_b X_{bdst}^{DB} \times \beta_b}{CPVH_v} \leq Y_{vdst}^{DB} \leq \frac{\sum_b X_{bdst}^{DB} \times \beta_b}{CPVH_v} + 1 \ \forall v,d,s,t \tag{4}$$

The number of the type v vehicle required to transfer batteries from the distribution centres to the battery swap stations in each period is calculated by constraint (4).

$$\frac{\sum_b X_{bsct}^{BC} \times \beta_b}{CPVH_v} \leq Y_{vsct}^{BC} \leq \frac{\sum_b X_{bsct}^{BC} \times \beta_b}{CPVH_v} + 1 \ \forall v,s,c,t \tag{5}$$

Constraint (5) calculates the number of the type v vehicle required to transfer the defective batteries from the battery swap stations to the collection centres in each period.

$$\frac{\sum_b X_{bct}^{CM} \times \beta_b}{CPVH_v} \le Y_{vct}^{CM} \le \frac{\sum_b X_{bct}^{CM} \times \beta_b}{CPVH_v} + 1 \ \forall v,c,t \tag{6}$$

Constraint (6) calculates the number of type v vehicles required to transfer the defective batteries from the collection centres to the manufacturing centre in each period.

$$\sum_b X_{bdt}^{MD} \times \alpha_b + M \times \left(1 - \theta_{dk}^{DC}\right) \ge LDC_k^{CP} \ \forall d,k,t \tag{7}$$

$$\sum_b X_{bdt}^{MD} \times \alpha_b \le UDC_k^{CP} + M \times \left(1 - \theta_{dk}^{DC}\right) \ \forall d,k,t \tag{8}$$

The appropriate capacity level for the established distribution centres is determined by constraints (7) and (8).

$$\sum_k \theta_{dk}^{DC} \le 1 \ \forall d \tag{9}$$

We are allowed to use one capacity level for each established distribution centre. Also, we should not define the capacity level for distribution centres that have not been established. This issue is considered in constraint (9).

$$\sum_{b,s} X_{bsct}^{BC} \times \alpha_b + M \times \left(1 - \theta_{ck'}^{CC}\right) \ge LCC_{k'}^{CP} \ \forall c,k',t \tag{10}$$

$$\sum_{b,s} X_{bsct}^{BC} \times \alpha_b \le UCC_{k'}^{CP} + M \times \left(1 - \theta_{ck'}^{CC}\right) \ \forall c,k',t \tag{11}$$

The appropriate capacity level for the established collection centres is determined by constraints (10) and (11).

$$\sum_{k'} \theta_{ck'}^{CC} \le 1 \ \forall c \tag{12}$$

Similarly, we can use one capacity level for each established collection centre. Also, we should not define the capacity level for collection centres that have not been established. Constraint (12) guarantees this.

$$\sum_d X_{bdt}^{MD} = \mu_{bt} \ \forall b, t = 1 \tag{13}$$

$$\sum_d X_{bdt}^{MD} = \sum_c X_{bc(t-1)}^{CM} + \mu_{bt} \ \forall b, t > 1 \tag{14}$$

The number of batteries shipped from the manufacturing centre to the distribution centres in the first and next periods is shown in constraints (13) and (14), respectively.

$$\lambda_{bdt} = X_{bdt}^{MD} - \sum_s X_{bdst}^{DB} \ \forall b,d,t = 1 \tag{15}$$

$$\lambda_{bdt} = \lambda_{bd(t-1)} + X_{bdt}^{MD} - \sum_s X_{bdst}^{DB} \ \forall b,d,t > 1 \tag{16}$$

The inventory level at the warehouses of the distribution centres for the first period and the next periods are calculated by constraints (15) and (16), respectively.

$$\sum_{d} X^{DB}_{bdst} \geq DBS_{bst} \ \forall b,s,t \tag{17}$$

Satisfying the demand for battery swap stations is considered in constraint (17).

$$\sum_{c} X^{BC}_{bsct} = RBS_{bst} \ \forall b,s,t \tag{18}$$

The number of defective batteries transferred from battery swap stations to collection centres is determined by constraint (18).

$$\sum_{s} X^{BC}_{bsct} = X^{CM}_{bct} \ \forall b,c,t \tag{19}$$

Constraint (19) indicates the inventory balance at the collection centres.

$$\sum_{i} \delta^{MN}_{i} = 1 \tag{20}$$

Constraint (20) states that exactly one type of IoT technology should be installed in the manufacturing centre.

$$\sum_{i} \delta^{DC}_{id} \leq 1 \ \forall d \tag{21}$$

$$\sum_{i} \delta^{CC}_{ic} \leq 1 \ \forall c \tag{22}$$

In established centres, exactly one type of IoT technology should be installed. This condition for distribution and collection centres is represented in constraints (21) and (22), respectively.

$$\delta^{DC}_{id} \leq \sum_{k} \theta^{DC}_{dk} \ \forall i,d \tag{23}$$

$$\delta^{CC}_{ic} \leq \sum_{k'} \theta^{CC}_{ck'} \ \forall i,c \tag{24}$$

The condition for installing IoT technology in the centres is that the desired centre is established. Constraints (23) and (24) guarantee this condition for distribution and collection centres, respectively.

$$\sum_{b} X^{MD}_{bdt} + \sum_{b,s} X^{DB}_{bdst} \leq M \times \sum_{i} \delta^{DC}_{id} \ \forall d,t \tag{25}$$

$$\sum_{b,s} X^{BC}_{bsct} + \sum_{b} X^{CM}_{bct} \leq M \times \sum_{i} \delta^{CC}_{ic} \ \forall c,t \tag{26}$$

Based on the location problem conditions, the batteries are transferred between echelons when the centres are established, and IoT technology is installed. This condition for distribution and collection centres is shown in constraints (25) and (26), respectively.

4 | THE MULTI-OBJECTIVE SOLUTION APPROACH

The literature review shows many methods for solving multi-objective decision-making problems. For example, when there are more than two objective functions, the GP method performs better than other methods (Zandkarimkhani et al., 2020). In addition, we use the LP-metric method proposed by Alinezhad et al. (2022) due to the difficulties in calculating the upper (lower) bound for the minimization (maximization) objective functions. Recently, Torabi and Hassini (2008) have presented a fuzzy multi-objective solution method called TH, which has received much attention from researchers. Considering the weight for the objective functions, solving the problem under uncertainty, obtaining the set of Pareto solutions, and drawing the Pareto frontier are among the unique features of this method, which is comprised of three steps:

- *Step 1*: Calculate the lower and upper bounds of the objective functions.
- *Step 2*: calculate the membership function of objective functions using Equation (27).

$$\xi_j(x) = \begin{cases} 1 & Z_j(x) > Z_j^U \\ 0 & Z_j(x) < Z_j^L \\ \dfrac{Z_j^U - Z_j(x)}{Z_j^U - Z_j^L}, & Z_j^L \leq Z_j(x) \leq Z_j^U \end{cases} \tag{27}$$

where $\xi_j(x)$ represents the membership function of objective function *j*. Also, Z_j^L and Z_j^U show the lower and upper bounds of objective function *j*, respectively.

- *Step 3*: Convert the multi-objective optimization model to a single-objective one using Equation (28).

$$\begin{aligned} & Max \psi \times \gamma_0 + (1-\psi) \times \sum_j \varpi_j \times \xi_j \\ & s.t. \\ & \gamma_0 \leq \xi_j \forall j \\ & System\ Constraints \end{aligned} \tag{28}$$

where γ_0 and ψ show the minimum satisfaction for objective functions and their weight, respectively. Also, the membership function weight of objective function *j* is shown by ϖ_j.

5 | CASE STUDY

In this section, we use expert knowledge and data from Lition Technology,[1] a large manufacturer of EV lithium-ion batteries in the Middle East, to validate the proposed model. This company currently manufactures about 0.9% of electric vehicle batteries globally, with a capacity of 8.5 Gigawatt hours. For two reasons, it was not possible to use the precise data of the case study to validate the proposed model. The first and most important reason is that, for security reasons, the company did not allow their detailed data to be published, and the second is that historical data was not available for all parameters. For this purpose, with the help of experts and available historical data, a simulation algorithm was developed to generate data. The simulation process is designed based on coefficients and approximations of real-world data. For a better understanding, consider the demand parameter. To generate the data of this parameter, historical documents of the company were examined in a specific time horizon, and the lower and upper bounds of the demand were determined in the investigated time horizon. Because we were not allowed to report the precise values of the demand parameter, we multiplied the identified lower and upper bounds into a coefficient. Then, by reviewing the literature, we found that researchers usually use uniform distribution functions to simulate parameters in supply chain network design models (Babaeinesami et al., 2022; Nosrati-Abarghooee et al., 2023); For this reason, we also applied these functions to simulate the parameters. The probability distribution functions used to simulate the data are shown in Table 2. One of the features of the proposed simulation algorithm is that a feasible solution space is formed for each desired value of the indices. Also, the parameters applied in the probability distribution functions are approximations of the real-world data, leading to the simulated data being close to the real-world data.

Ten test problems in different dimensions are generated using the proposed simulation algorithm, and the performance of the proposed model is evaluated for these problems. The size of these test problems is presented in Table 3.

Consequently, the presented bi-objective model is transformed into a single-objective model, and the single-objective model is run for 10 test problems in GAMS software. This process is described below:

- *Step 1*: In this step, each objective function's upper and lower bounds are calculated using the lexicographic method. To calculate the lower bound of the first (second) objective function, we run the model for the first (second) objective function and ignore the second (first) objective function. In this instance, the value obtained for the first (second) objective function is considered the lower bound of the first (second) objective function. To calculate the upper bound of the first (second) objective function, we run the model for the first (second) objective function on the condition that the second (first) objective function is not greater than its lower bound. Table 4 shows the upper and lower bounds of the objective functions.
- *Step 2*: After determining the lower and upper bounds of the objective functions of each problem, we calculate the membership functions with the help of Equation (27). Two membership functions are calculated for each simulated problem, one for the first objective function and the

TABLE 2 Data simulation algorithm using probabilistic distribution functions.

Indices/parameters	Probabilistic distribution functions for data simulation
b,d,c,k,k',s,v,i,t	Optional values
DBS_{bst}	$Round\,(uniform(90,110))$
RBS_{bst}	$Round\,(Uniform(32,45))$
α_b	$Uniform\,(0.35,0.5)$
β_b	$Uniform\,(200,300)$
$LDC_k^{CP},LCC_{k'}^{CP}$	0
UDC_k^{CP}	$If\left(\begin{array}{l} k=1, \\ UDC_k^{CP}=Round\left(\frac{\sum_{b,s,t} DBS_{bst}\times\alpha_b}{T}\right); \\ else \\ UDC_k^{CP}=Round\left(1.2\times UDC_{k-1}^{CP}\right) \end{array}\right)$
$UCC_{k'}^{CP}$	$If\left(\begin{array}{l} k'=1, \\ UCC_{k'}^{CP}=Round\left(\frac{\sum_{b,s,t} RBS_{bst}\times\alpha_b}{T}\right); \\ else \\ UCC_{k'}^{CP}=Round\left(1.2\times UCC_{k'-1}^{CP}\right) \end{array}\right)$
$CPVH_v$	$If\left(\begin{array}{l} v=1, \\ CPVH_v=3000 \\ else \\ CPVH_v=CPVH_{v-1}+500; \end{array}\right)$
MN_{bt}^{CST}	$Round(uniform(800,1100))$
RMN_{bt}^{CST}	$Round(uniform(300,450))$
$PDC_{bdt}^{CST},PCC_{bct}^{CST}$	$Uniform(2,3)$
HDC_{bdt}^{CST}	$Uniform(7,10)$
SDC_{dk}^{CST}	$Round(uniform(30000,36000))$
$SCC_{ck'}^{CST}$	$Round(uniform(24000,28000))$
$IoT_i^{MN},IoT_{id}^{DC},IoT_{ic}^{CC}$	$Round(uniform(8000,9000))$
TG_t	$Uniform(2.5,3.5)$
IoT_i^{EN}	$Uniform(0.03,0.05)$
PEN	0.168
DIS_d^{MD}	$Uniform(65,90)$
DIS_{ds}^{DB}	$Uniform(8,15)$
DIS_{sc}^{BC}	$Uniform(25,40)$
DIS_c^{CM}	$Uniform(35,60)$
RVH_v	$Uniform(0.8,1.2)$
$COVH_v$	$Uniform(0.45,0.5)$
$COIoT$	0.37

other for the second objective function (e.g., see the upper and lower bounds of the first objective function related to test problem 1 (TPR1) in Table 4). These bounds are used to form the membership function for the first objective function (TPR1). For this purpose, we subtract Z_1 from the upper bound and divide the result by the difference between the upper and lower bounds. In the same way, we calculate the membership functions for other objective functions of the simulated problems presented in Table 5.

TABLE 3 Size of the test problems.

Test problem	b	d	c	k	k'	s	v	i	t
TPR1	1	2	2	1	1	3	1	1	2
TPR2	1	3	2	2	2	4	2	2	2
TPR3	2	3	3	2	2	5	2	2	3
TPR4	2	4	3	2	2	6	3	2	4
TPR5	3	4	4	3	2	7	3	3	4
TPR6	3	4	4	3	3	7	3	3	5
TPR7	3	5	4	3	3	8	4	4	5
TPR8	4	5	5	4	3	8	4	4	6
TPR9	4	6	5	4	4	9	4	4	6
TPR10	5	7	5	4	4	10	5	5	7

TABLE 4 The upper and lower bounds of objective functions.

Test problem	Z_1^L	Z_1^U	Z_2^L	Z_2^U
TPR1	642,700	667,363	3049	3101
TPR2	828,759	906,776	5708	5780
TPR3	2,551,976	2,759,502	24,089	24,932
TPR4	3,846,564	4,140,647	48,327	49,628
TPR5	6,388,476	6,679,367	102,653	103,163
TPR6	8,241,750	8,900,998	124,371	128,185
TPR7	9,414,517	10,151,028	170,947	173,265
TPR8	14,932,313	15,991,823	263,025	283,934
TPR9	16,522,047	17,956,184	319,441	320,041
TPR10	28,582,495	29,374,301	571,892	586,573

TABLE 5 The membership functions of the objective function for the test problems.

Test problem	ξ_1	ξ_2
TPR1	$\frac{667363-Z_1}{667363-642700}$	$\frac{3101-Z_2}{3101-3049}$
TPR2	$\frac{906776-Z_1}{906776-828759}$	$\frac{5780-Z_2}{5780-5708}$
TPR3	$\frac{2759502-Z_1}{2759502-2551976}$	$\frac{24932-Z_2}{24932-24089}$
TPR4	$\frac{4140647-Z_1}{4140647-3846564}$	$\frac{49628-Z_2}{49628-48327}$
TPR5	$\frac{6679367-Z_1}{6679367-6388476}$	$\frac{103163-Z_2}{103163-102653}$
TPR6	$\frac{8900998-Z_1}{8900998-8241750}$	$\frac{128185-Z_2}{128185-124371}$
TPR7	$\frac{10151028-Z_1}{10151028-9414517}$	$\frac{173265-Z_2}{173265-170947}$
TPR8	$\frac{15991823-Z_1}{15991823-14932313}$	$\frac{283934-Z_2}{283934-263025}$
TPR9	$\frac{17956184-Z_1}{17956184-16522047}$	$\frac{320041-Z_2}{320041-319441}$
TPR10	$\frac{29374301-Z_1}{29374301-28582495}$	$\frac{586573-Z_2}{586573-571892}$

- *Step 3*: This step deals with transforming the bi-objective model into a single-objective model by the membership functions presented in Table 5 and Equation (28). For example, in the following, the single objective model for test problem 5 (TPR5) is given. By running the single-objective model using the CPLEX solver in GAMS software, the optimal values of the decision variables and objective functions are determined for each test problem. It should be noted that the value of the parameter ψ is considered to be 0.25; because Torabi and Hassini (2008) have clearly stated that the value of this parameter should be smaller than 0.3, and in the literature, the value of this parameter is considered

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TABLE 6 The optimal value of objective functions for test problems.

Test problem	Z_1^*	Z_2^*	Runtime (second)
TPR1	642,894	3069	3.05
TPR2	831,082	5749	15.73
TPR3	2,554,687	24,169	46.86
TPR4	3,862,629	48,527	94.53
TPR5	6,415,263	102,802	165.94
TPR6	8,287,276	125,077	288.16
TPR7	9,453,945	171,634	428.82
TPR8	15,071,193	264,312	862.10
TPR9	16,717,105	319,811	1174.25
TPR10	28,729,182	574,839	1483.89

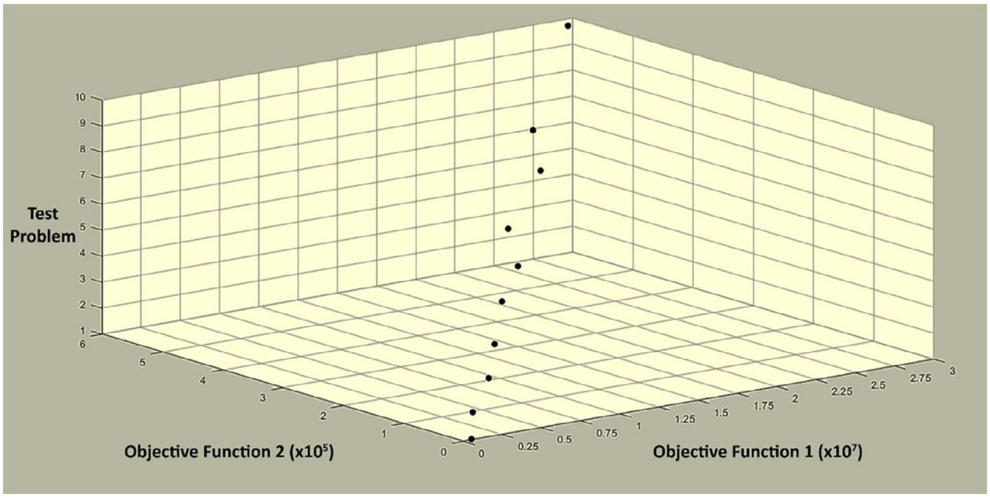

FIGURE 2 Increasing trend of objective functions with increasing problem size.

between 0.2 and 0.3 (Dehshiri et al., 2022; Mohammadi et al., 2020). The values of ϖ_1 and ϖ_2 are also considered 0.6 and 0.4, respectively, based on the experts' opinions. Of course, in the process of sensitivity analysis in the next section, the proposed model has been implemented for different values of parameters ϖ_1 and ϖ_2 so that instead of one solution, a set of Pareto solutions is available to the experts. The optimal value of objective functions for test problems is presented in Table 6. Also, Table 6 shows that increasing problem size increases the value of both objective functions. Figure 2 illustrates the increasing trend of the objective functions as the problem size increases.

$$
\begin{aligned}
& Max\, 0.25 \times \gamma_0 + 0.75 \times (0.6 \times \xi_1 + 0.4 \times \xi_2) \\
& s.t. \\
& \xi_1 = \frac{6679367 - Z_1}{6679367 - 6388476} \\
& \xi_1 = \frac{103163 - Z_2}{103163 - 102653} \\
& \gamma_0 \leq \xi_1 \\
& \gamma_0 \leq \xi_2 \\
& \text{Constraints}\,(3)\,\text{to}\,(26)
\end{aligned}
\tag{29}
$$

In this study, the size of problems whose runtime in GAMS software is not more than 1500 s was investigated (see Table 6). The results presented in this table show that increasing the size of the problem has a direct effect on increasing the runtime. As the problem size increases, the

TABLE 7 The optimal value of objective functions for different scenarios.

Scenario	ϖ_1	ϖ_2	Objective function 1	Objective function 2
SCNR1	0.35	0.65	6,637,282	102,658
SCNR2	0.4	0.6	6,598,137	102,680
SCNR3	0.45	0.55	6,548,711	102,712
SCNR4	0.5	0.5	6,483,295	102,741
SCNR5	0.55	0.45	6,438,416	102,783
SCNR6 (TPR5)	0.6	0.4	6,415,263	102,802
SCNR7	0.65	0.35	6,400,189	102,884
SCNR8	0.7	0.3	6,398,155	102,973
SCNR9	0.75	0.25	6,391,220	103,061

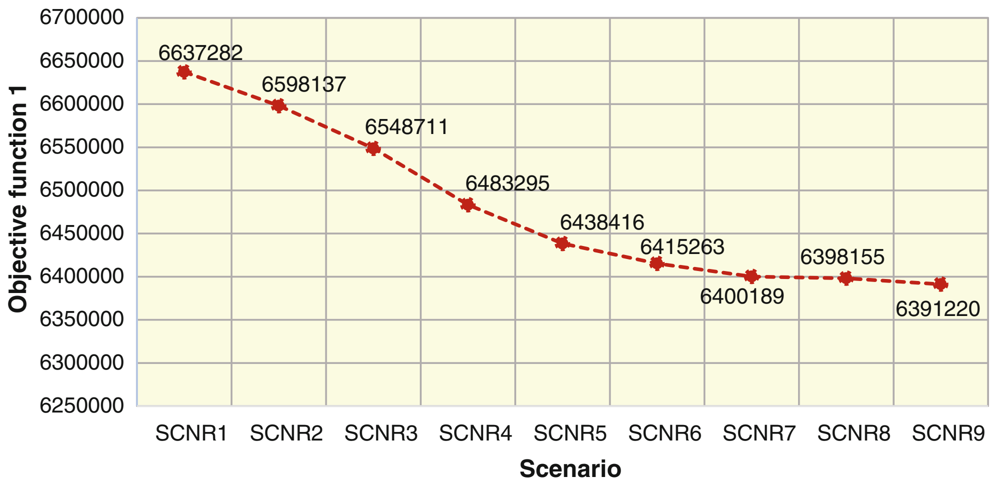

FIGURE 3 The trend of the first objective function in the sensitivity analysis process.

3 V's of big data (i.e., Velocity, Volume, and Variety) increase simultaneously, effectively increasing the runtime. Parameters include the cost of manufacturing and remanufacturing batteries, the cost of processing batteries at the distribution and collection centres, the cost of holding batteries at the warehouses of distribution centres, the cost of establishing centres, the demand for battery swap stations, etc., impacts on the velocity of big data. The number of nine indices effective in the volume of big data, number of batteries, distribution and collection centres, capacity level for the distribution and collection centres, battery swap stations, vehicles, IoT technologies, and periods are included in this model. These mentioned factors affect the variety of big data. Accordingly, with the increase of the various dimension, the velocity dimension also experiences an enormous increase. In other words, the volume of data increases, and, thereby, big data are produced. As mentioned above, the volume of the already produced data directly influences the runtime of this model.

6 | SENSITIVITY ANALYSIS

This study formulated a bi-objective optimization model to structure an SCSC network for managing the EV lithium-ion battery industry under uncertainty and a big data environment. Its efficiency was evaluated using 10 simulated test problems. In this section, we will examine the results' validity using the sensitivity analysis process of the objective functions' coefficients. When we increase the coefficient of the first (second) objective function, the coefficient of the second (first) objective function decreases. Considering that both objective functions are minimized, it is anticipated that the value of an objective function whose coefficient has increased will not increase. The value of an objective function whose coefficient has decreased will not decrease. Based on this, we define scenarios based on changing the coefficients of the objective functions and evaluate the performance of the presented model and solution method for these scenarios. These scenarios and the optimal value of the first and second objective functions for these scenarios are indicated in Table 7. It should be emphasized that test problem 5 (TPR5) was used to implement the sensitivity analysis process. The behaviour of the objective functions for all scenarios is depicted in Figures 3 and 4, respectively. Also, the Pareto frontier resulting from these scenarios is shown in Figure 5.

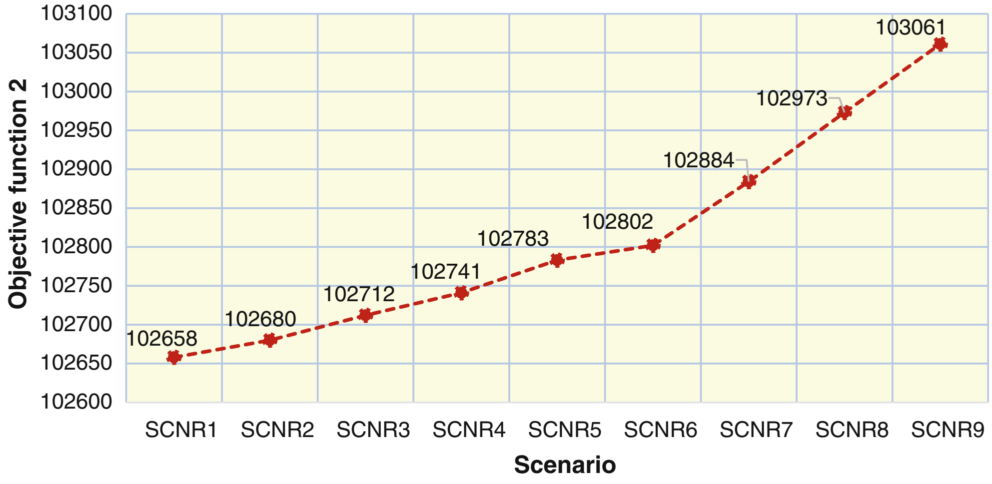

FIGURE 4 The trend of the second objective function in the sensitivity analysis process.

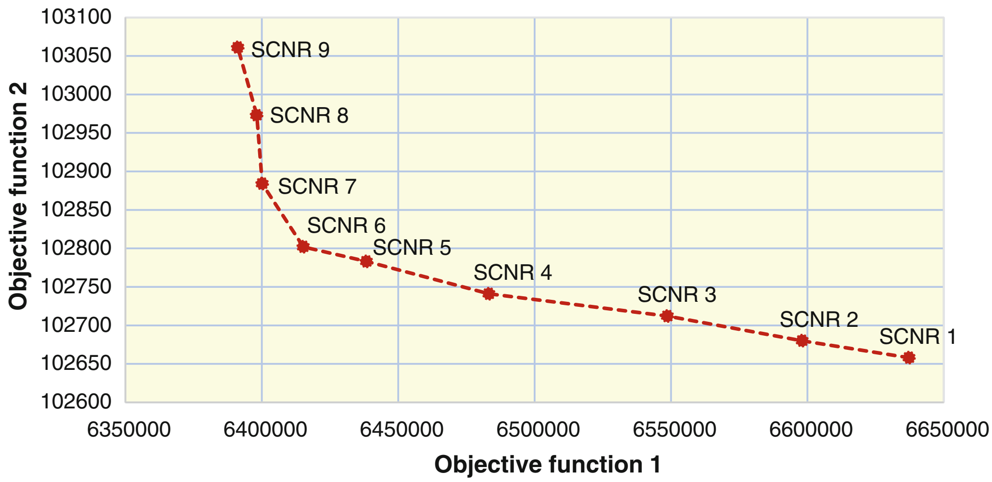

FIGURE 5 Pareto frontier resulted from the sensitivity analysis process.

As seen in Table 7 and Figures 3 and 4, by raising the coefficient of objective function 1 and reducing the coefficient of objective function 2 simultaneously, the optimal value of objective function 1 has decreased, and the optimal value of objective function 2 has increased, respectively. The sensitivity analysis of the coefficients of the objective functions revealed that the behaviour of the proposed model is reasonable and follows the expectations. Therefore, the results obtained from the proposed model are confirmed.

7 | COMPARATIVE ANALYSIS

This paper used a priori method to solve the proposed bi-objective optimization model. In the priori methods, decision makers' preferences are considered as weights in the objective functions. Priori methods allow obtaining a set of Pareto solutions by changing the weights of the objective functions. Another category of methods is the posteriori methods that do not require expert preferences and are used when the goal is to find a set of Pareto efficient solutions without the presence of experts. The epsilon-constraint method is one of the most well-known posteriori methods, which has received much attention from researchers. In this method, the objective function with the highest priority is considered the main objective function of the model, and other objective functions are transferred to the set of constraints (Bouziaren & Aghezzaf, 2018). Issues and features related to the epsilon-constraint method are presented in detail in the paper by Mavrotas (2009). In this section, we will solve the proposed bi-objective model using the augmented epsilon-constraint method (AUGMECON) developed by Mavrotas (2009). Below is the process of implementing this method on problem 5 (TPR5).

The first step to using AUGMECON is determining the upper and lower bounds of the objective functions and structuring the payoff table. A lexicographic method is described in the first step of the case study section. Table 4 shows the payoff table. Based on AUGMECON presented in Equation (30), one objective function is considered the main objective function, and the other objective function(s) are transferred to the constraint set.

$$
\begin{aligned}
& Min\left(Z_1-\kappa\times\left(\frac{\varphi_2}{r_2}+\ldots+\frac{\varphi_p}{r_p}\right)\right)\\
& s.t.\\
& Z_2+\varphi_2=eps_2\\
& \vdots\\
& Z_j+\varphi_j=eps_j\\
& \vdots\\
& Z_p+\varphi_p=eps_p\\
& \varphi_2,\ldots,\varphi_p\geq 0
\end{aligned}
\tag{30}
$$

where $\kappa=\left[10^{-6},10^{-3}\right]$; φ_j is the Slack variable for objective function j; $r_j=Z_j^U-Z_j^L$; eps_j is the right-hand side of constrained objective function j.

Equation (31) is applied to calculate eps_j:

$$
eps_j=Z_j^L+\frac{r_j}{\Omega_j}\times q\ \forall q=0,1,\ldots,\Omega_j
\tag{31}
$$

Ω_j is a parameter related to the number of grid points. For example, in a bi-objective model, if the decision maker wants to have m grid points, s/he must set Ω_2 equal to $m-1$. The proposed model presented in Equation (30) can be expanded using AUGMECON as follows:

$$
\begin{aligned}
& Min\left(Z_1-\kappa\times\left(\frac{\varphi_2}{r_2}+\ldots+\frac{\varphi_p}{r_p}\right)\right)\\
& MinZ_1=\sum_{b,t}MN_{bt}^{CST}\times\mu_{bt}+\sum_{b,c,t}RMN_{bt}^{CST}\times X_{bct}^{CM}+\sum_{b,d,t}PDC_{bdt}^{CST}\times X_{bdt}^{MD}+\\
& \sum_{b,d,t}HDC_{bdt}^{CST}\times\lambda_{bdt}+\sum_{d,k}SDC_{dk}^{CST}\times\theta_{dk}^{DC}+\sum_{b,s,c,t}PCC_{bct}^{CST}\times X_{bsct}^{BC}+\sum_{c,k'}SCC_{ck'}^{CST}\times\theta_{ck'}^{CC}+\\
& \sum_{i}IoT_i^{MN}\times\delta_i^{MN}+\sum_{i,d}IoT_{id}^{DC}\times\delta_{id}^{DC}+\sum_{i,c}IoT_{ic}^{CC}\times\delta_{ic}^{CC}+\sum_{b,t}TG_t\times\mu_{bt}+\\
& \sum_{i}PEN\times IoT_i^{EN}\times\left(\sum_{b,d,t}X_{bdt}^{MD}+\sum_{b,d,s,t}X_{bdst}^{DB}+\sum_{b,s,c,t}X_{bsct}^{BC}+\sum_{b,c,t}X_{bct}^{CM}\right)+\\
& \sum_{v,d,t}RVH_v\times DIS_d^{MD}\times Y_{vdt}^{MD}+\sum_{v,d,s,t}RVH_v\times DIS_{ds}^{DB}\times Y_{vdst}^{DB}+\\
& \sum_{v,s,c,t}RVH_v\times DIS_{sc}^{BC}\times Y_{vsct}^{BC}+\sum_{v,c,t}RVH_v\times DIS_c^{CM}\times Y_{vct}^{CM}-\kappa\times\frac{\varphi_2}{103163-102653}
\end{aligned}
\tag{32}
$$

s.t.

$$
\begin{aligned}
& \sum_{i}COIoT\times IoT_i^{EN}\times\left(\sum_{b,d,t}X_{bdt}^{MD}+\sum_{b,d,s,t}X_{bdst}^{DB}+\sum_{b,s,c,t}X_{bsct}^{BC}+\sum_{b,c,t}X_{bct}^{CM}\right)+\\
& \sum_{v,d,t}COVH_v\times DIS_d^{MD}\times Y_{vdt}^{MD}+\sum_{v,d,s,t}COVH_v\times DIS_{ds}^{DB}\times Y_{vdst}^{DB}+\\
& \sum_{v,s,c,t}COVH_v\times DIS_{sc}^{BC}\times Y_{vsct}^{BC}+\sum_{v,s,c,t}COVH_v\times DIS_c^{CM}\times Y_{vct}^{CM}+\varphi_2=eps_2\\
& \text{Constraints (3) to (26)}
\end{aligned}
\tag{33}
$$

Nine scenarios (grid points) were considered in the sensitivity analysis section to draw the Pareto frontier. We consider nine grid points to draw the Pareto frontier in this section. In this regard, eps_2 for each grid point is calculated using Equation (31), which is shown in Table 8. The optimal values of objective functions are calculated for each grid point by running the model in GAMS software using the CPLEX solver. Table 8 shows the optimal values of the objective functions for the nine grid points. The Pareto frontier obtained from these grid points is depicted in Figure 6.

TABLE 8 The obtained results from AUGMECON.

Grid point	eps_2	Z_1^*	Z_2^*
G1	$102653+0\times\frac{510}{8}=102653$	6,679,367	102,653
G2	$102653+1\times\frac{510}{8}=102716.75$	6,548,711	102,712
G3	$102653+2\times\frac{510}{8}=102780.5$	6,468,190	102,769
G4	$102653+3\times\frac{510}{8}=102844.25$	6,408,211	102,825
G5	$102653+4\times\frac{510}{8}=102908$	6,400,189	102,884
G6	$102653+5\times\frac{510}{8}=102971.75$	6,399,172	102,964
G7	$102653+6\times\frac{510}{8}=103035.5$	6,394,901	103,014
G8	$102653+7\times\frac{510}{8}=103099.25$	6,389,971	103,098
G9	$102653+8\times\frac{510}{8}=103163$	6,388,476	103,163

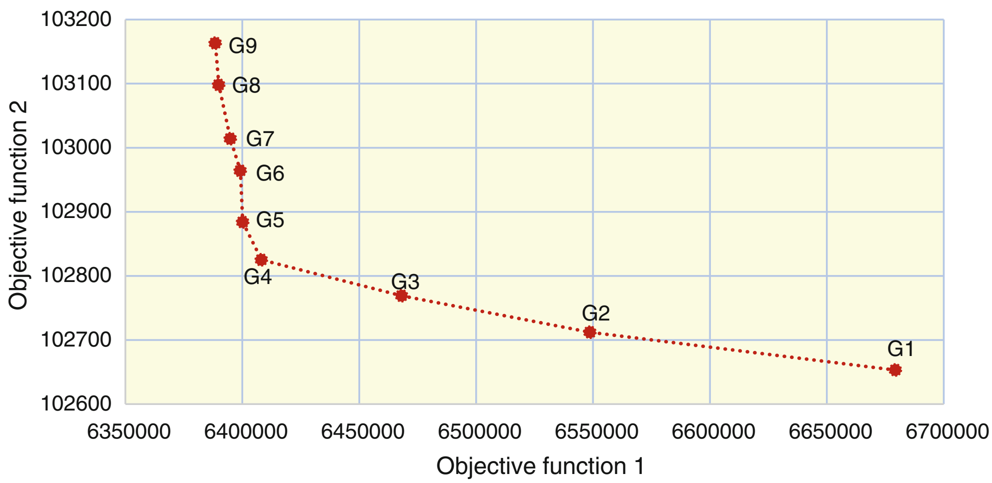

FIGURE 6 Pareto frontier obtained from AUGMECON.

A two-by-two comparison of the results obtained for the grid points in Table 8 reveals that all the solutions are efficient; because other grid points do not dominate the solutions of any grid point. Now we will examine the performance of TH method compared to AUGMECON. By comparing the results obtained for TH method (see Table 7) and the results obtained for AUGMECON shown in Table 8, it can be understood that both methods have good efficiency; because they have presented the same results in two grid points, and in other grid points, none of the solution set of TH method is dominated by the solution set of AUGMECON. In general, it can be concluded that both methods are sufficiently efficient, with the difference that the TH method is used when it is possible to weigh the objective functions. If experts' preferences are not important before running the model, AUGMECON is used.

8 | DISCUSSION

Providing solutions for decarbonization in the transportation sector is a targeted strategy to reduce greenhouse gas emissions (Hill et al., 2019). The use of EVs is one of these strategies that greatly helps reduce greenhouse gas emissions and is considered a big step toward sustainability. It is expected that in the coming years, due to the increasing pressure of environmental policies and the pull of customers, the demand for EVs will increase exponentially, leading to an exponential increase in the demand for lithium-ion batteries (Jones et al., 2020). The demand for raw materials such as lithium and cobalt will increase, bringing concerns (Lander et al., 2021). Rapid consumption of resources and encountering a large amount of lithium-ion batteries that have reached the end of their life are among these concerns (Harper et al., 2019). In other words, although using EVs is a good strategy for reducing greenhouse gases, it brings the abovementioned problems. Now the question arises, how to reduce waste batteries and resource consumption at the same time?

The most suitable solution is moving toward the CE and applying the recycling process. Because the number of retired batteries is relatively low, the manufacturers do not have a great desire to recycle them; recycling costs are high, and their profit is low (Dunn et al., 2022). But the disadvantages of releasing these batteries into the environment are so great that the high cost of recycling cannot be a logical justification for not recycling them. Governments also often provide incentives for consumers to collect as many lithium-ion batteries as possible and facilities for manufacturers to recycle these batteries as much as possible. For example, buying retired batteries from consumers at an attractive price can be one of the incentives for the maximum collection of lithium-ion batteries. Increasing consumers' environmental awareness regarding the harm of disposed batteries to the health of living organisms and the environment can be another incentive.

Therefore, in this paper, a zero-waste supply chain network was configured with the help of CE concepts to manage the production, distribution, and recycling of EV lithium-ion batteries. The proposed model's first objective function considers the network's economic aspect and the total strategic and operational costs are minimized simultaneously. The environmental aspect of the network is included in the second objective function. This objective function minimizes CO2 emissions from transportation activities and applies IoT technology. Two multi-objective solution approaches, including the TH method and AUGMECON, were applied to solve the proposed bi-objective MILP model. Both proposed approaches provide an upper and lower bound for the simulated problems and a set of Pareto-efficient solutions to create a trade-off between the two objective functions.

9 | CONCLUSION

The main purpose of this research is to design a circular zero-waste supply chain for managing spent EV lithium-ion batteries. To this end, a virtual SCSC was structured using mathematical programming tools and with the help of IoT and big data concepts considering reverse and forward flows in the EV lithium-ion batteries industry. The proposed model includes two objective functions. The first objective function minimizes the sum of the strategic and operational costs. The second objective function deals with minimizing CO_2 emissions caused by energy consumption by IoT technology and transportation. We used the TH method to transform the presented bi-objective model into a single-objective model. Due to the limited access to data, a simulation algorithm was presented with the help of some historical data and expert knowledge of an EV lithium-ion batteries manufacturing company in the Middle East using probability distribution functions. The proposed simulation algorithm is designed so that we always encounter a feasible solution space for each desired value of the indices. Ten test problems were simulated to examine the proposed model performance in GAMS software. Finally, the correctness of the results was confirmed using the sensitivity analyses on the coefficients of the objective functions.

In this paper, a novel MILP model was formulated to design a zero-waste CLSC network in the EV lithium-ion batteries industry. The proposed model can solve small and medium-sized problems in a logical time using GAMS software and achieve global optimal solutions. But it is unable to solve large-size problems. For this purpose, it is suggested that future studies focus on developing heuristic or meta-heuristic algorithms to solve this problem in large sizes. Non-dominated sorted genetic algorithm II (NSGA II) and multi-objective particle swarm optimization (MOPSO) are among the most widely used and well-known algorithms that are suggested to be used to solve this problem.

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY STATEMENT

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

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ENDNOTE

[1] The name and location are changed to protect the anonymity of the company.

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