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Multi-objective Design of Sustainable Closed-loop Supply Chain Considering Social Benefits: Metaheuristic Optimization Approaches

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Abstract –In line with growing global concerns regarding environmental and social issues, supply chain corporations are improving their environmental and social performances. The optimal design of a closed-loop supply network must conceive various aspects, leading to a multi-objective problem. This study develops a mixed-integer linear programming model to provide an integrated supply network with a particular focus on sustainability. Besides cost efficiency, energy consumption, and job creation are incorporated as additional objective functions. This article uniquely introduces the training of supply chain employees as part of the developed model to address social responsibility. The Non-Dominated Sorting Genetic Algorithm-II (NSGA-II) and Multiple Objective Particle Swarm Optimization (MOPSO) are employed to solve the multi-objective problem. The numerical examples for cost and energy values are based on real data. The results demonstrate the significant effect of returned product recovery on cost reduction in the network and changes in energy consumption at different levels. NSGA-II and MOPSO yield a set of optimal solutions that increase the flexibility of decision-makers. Indeed, a set of Pareto solutions reveals a conflict between the objective functions and allows the network to be highly effective in decision-making under different conditions and policies.

***Keywords**– Multi-objective programming, MOPSO, NSGA-II, Social responsibility, Sustainable closed-loop supply chain design.*

I. INTRODUCTION

Recent legislative changes and growing consumer awareness of sustainability (Foroozesh & Karimi, 2022; Ramezani et al., 2024) have significantly influenced manufacturing companies' perspectives on sustainability issues (Bahrampour et al., 2022; Ehsanifar et al., 2023). Sustainability aims to fulfill the needs of the present moment without jeopardizing future generations' ability to meet their needs (Jafarzadeh et al., 2022; Taghipour, Fooladvand, et al., 2023). The three pillars of sustainability (economic, environmental, and social) highlight the importance of holistic considerations in production processes (Taghipour et al., 2024). The economic factors, despite being critically important, cannot ensure the success of a system (Nayeri et al., 2022). The shift in consumer focus towards environmental sustainability has prompted companies to prioritize this aspect, enhancing their competitiveness in the market (Dehshiri & Amiri, 2024; Sarkis, 2003, 2012). Environmental responsibility includes managing the use of

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resources, renewable and non-renewable energy consumption, pollution, waste, and effluents (Olfati & Paydar, 2023). In recent literature, great attention has been paid to environmental issues, particularly studies examining the green supply chain (Khorshidvand et al., 2021). However, the social aspect of sustainability has received less attention in these articles (Mohammadi & Nikzad, 2023; Taghipour, Ramezani, et al., 2023).

In contemporary society, there is an increased awareness of social values among consumers. Social responsibility is understood as the ongoing commitment of businesses to act ethically, support economic development, and enhance the well-being of their employees, families, local communities, and society as a whole (Dehghanian & Mansour, 2009). This suggests that in addition to economic and environmental issues, the production network's social responsibility plays an equally critical role in the consumers' choices (Taghipour, Sohrabi, et al., 2023; Yan et al., 2021). Considering social factors in the design of a logistics network can enhance its public perception and, in turn, increase its competitiveness. However, the prevalence of qualitative over quantitative aspects when addressing social responsibilities in sustainable supply chain management (Taghipour, Foukolaei, et al., 2023) presents significant challenges for researchers, particularly in modeling these aspects (Keshavarz-Ghorbani & Pasandideh, 2023). There is a shortage of studies focusing on the social aspects of supply chain networks. Previous studies primarily modeled job creation through networks as an indicator of social responsibility. Although increasing employee numbers can enhance a network's social status, it also raises operational costs. Therefore, identifying an optimal number of employees is crucial in balancing these factors (Seydanlou et al., 2022). Other aspects of social responsibility have rarely been discussed in supply chain studies. One of the issues mentioned in the social factor is the employees and their working conditions. Sufficient knowledge about safety and their tasks has significant effects on the physical and mental health of workers. The solution to achieve this knowledge is to include training.

In the increasingly competitive global market, the success of companies is directly related to the cost of finished products, their quality, and the satisfaction of consumers. Supply chain management has recognized the solution to reduce the cost, increase the quality of products as well as increase consumer satisfaction. The fierce competition between companies, global marketing, shorter product life, and increased customer expectations have forced companies to pay more attention to the SC (Beamon, 1998). An SC is a network for monitoring and managing products, from raw materials to manufacturing, transportation, inventory, and retail distribution to customers (Atabaki et al., 2017; Hashemi et al., 2015). Designing an integrated and efficient supply chain network is a critical issue for companies' prosperity, increasing competitive potency, and user satisfaction (Fathollahi-Fard et al., 2018). Supply chain network design (SCND) includes three categories: forward supply chain, reverse supply chain, and closed-loop supply chain (Akbari-Kasgari et al., 2020; Boronoos et al., 2019; Samadi et al., 2018).

The traditional definition of the supply chain considers the direct flow of materials from the first node of the network (suppliers) to final product delivery to the customers without any plan for these products afterward (Atabaki et al., 2018; Garcia & You, 2015). Ecological concerns about the severe exploitation of natural resources leading to the energy deprivation of future generations and the harmful effects of products' end-of-life have become imperative matters for governments as well as consumers. The implementation of a reverse supply chain, closed-loop supply chain (CLSC), and return of products after their end-of-use, have been introduced as practical solutions to this problem (Keshavarz-Ghorbani & Pasandideh, 2023). Reverse supply chain is defined as the "movement of material from the point of consumption toward the point of origin with the aim of re-valuing or proper disposal and destruction" (Rogers & Tibben-Lembke, 2001). The concept of CLSC has been considered as a result of the need for simultaneous and integrated management of both direct and reverse supply chains. It can be noted that due to the partial return of products to the production cycle, the design of CLSC causes the return of financial resources and raw materials. It also allows for the safe disposal of waste, which facilitates the sustainability of products to some extent.

Addressing sustainability turns supply chain design into a multi-objective problem. This is unlike the single-objective approach often seen in existing research, which is a notable limitation. Many studies emphasize the importance of integrated supply chain design, but typically only focus on limited levels of the chain. Exact solution methods are effective for small models but become inefficient as the complexity increases due to more levels and variables. This leads to NP-hard problems. To address these complex scenarios, heuristic and metaheuristic algorithms such as genetic algorithms, Particle Swarm Optimization, and tabu search have been developed (Harrison et al., 2004; Watson et al., 2013).

This study focuses on designing and optimizing a CLSC with sustainability considerations. It addresses strategic and operational decision-making for supply chain managers, including facility location, vehicle routing problems, order allocation, and the management of product lifecycles from collection through recycling to safe disposal. The model specifies manufacturing technologies and supports transportation planning with a fleet vehicle analysis. The primary objectives are to minimize network costs and energy consumption while maximizing job creation to enhance the network's social status. Furthermore, it highlights the importance of employee training to prevent production inefficiencies, to reduce accidents, and to avert financial losses. This emphasis aims to boost social benefits and enhance the network's reputation among consumers.

1. **Sustainable Supply Chain Design**: The study presents a sustainable supply chain with a complex reverse flow model by integrating energy consumption and job opportunities aiming to increase environmental protection, preserve resources for future generations, and fulfill social responsibilities
2. **Employee Training Integration**: Incorporating employee training into the supply chain mathematical model to improve social responsibility and enhance the network's social status, a facet rarely addressed in past studies.
3. **Optimized Transportation System**: Proposing a transportation system with a heterogeneous vehicle fleet to achieve the desired number of trips, optimizing both transportation costs and energy consumption.
4. **Metaheuristic Algorithms Application**: Utilizing two metaheuristic algorithms with unique encoding-decoding procedures to cope with the complexity of the supply chain configuration to solve the CLSC problem. This provides a Pareto solution set that assists managers in making informed decisions at both strategic and operational levels.

These contributions collectively aim to develop a sustainable, and socially responsible closed-loop supply chain model flow to maximize the use of returned products and achieve a total circularity that addresses the contemporary challenges faced by supply chain managers. The rest of the paper is organized as follows: Section II conducts a literature review on the subject. Problem definition and mathematical models are provided in section III. Sections IV and V present the methodology, and results and discussions, respectively. Section VI concludes the paper by discussing research limitations as well as future research directions.

II. LITERATURE REVIEW

Supply chain management is essential for the effective delivery of products from production to consumption, involving complex logistics and coordination across multiple stages. These include raw material sourcing, manufacturing, and distribution (Dossa et al., 2022; Gebhardt et al., 2022; Pasandideh et al., 2015; Zhao et al., 2016). It plays a crucial role in ensuring that consumer demands are met efficiently, thereby enhancing satisfaction and competitiveness (Pasandideh et al., 2023). The significance of integrated supply chain management is particularly evident in maintaining network profitability and stability during crises, as demonstrated in studies focusing on the food supply chain (Rahbari et al., 2023b).

A closed-loop supply chain (CLSC) incorporates both forward and reverse logistics to manage the lifecycle of a product from production to post-use recovery (Rahbari et al., 2024). This system is geared towards sustainability by reintroducing end-of-life products into the production cycle through remanufacturing, which helps in resource conservation and energy sustainability (Battini et al., 2017; Braz et al., 2018; Mehrjerdi & Shafiee, 2021; Raza, 2020; Yun et al., 2020). The adoption of CLSC models has led to significant reductions in waste and product costs, improvements in service delivery, and improvements in customer loyalty, all the while reducing environmental effects (Ferguson & Souza, 2010). Both governments and businesses have focused increasingly on CLSCs within the broader context of circular economy strategies to minimize the depletion of natural resources and address economic, environmental, and social challenges (Govindan et al., 2020; Shabbir et al., 2021; Yavari & Geraeli, 2019; Yoo & Cheong, 2021).

CLSCs are increasingly recognized for enhancing sustainability by integrating economic, environmental, and social dimensions. Goodarzian et al. (2020) and Mohtashami et al. (2020) highlight the significant environmental impacts influencing human life, while Winkler (2011) discusses sustainable supply chain networks as effective for economic and environmental transformation towards a circular economy. Dou and Cao (2020) explore the performance of various CLSC configurations, including retailer, manufacturer, and third-party collection points that support remanufacturing. De Giovanni (2022) discusses blockchain technology's potential to enhance circular economy features within CLSC frameworks. Yavari and Geraeli (2019) address resilience in green CLSCs for perishable goods, minimizing costs and emissions despite risks like power disruptions. Zhang et al. (2019) present a multi-echelon model that measures sustainability through reduced costs, lower carbon emissions, and enhanced social outcomes, which shows the interdependence of these aspects in CLSC operations.

Recent studies in CLSC literature have highlighted various dynamics within the consumer electronics and automotive sectors, particularly focusing on hybrid systems and multiple product recovery options, such as repair and remanufacturing, to mitigate issues like the bullwhip effect (Battini et al., 2017; Guan et al., 2020). Research has explored the placement and quantity of these recovery options and their impact on supply chain dynamics, including demand shifts and return rates across different echelons (Yavari & Zaker, 2019). Simulation results have shown significant reductions in bullwhip and inventory volatility in CLSC setups compared to traditional open-loop systems. Additionally, studies have examined the environmental and economic implications of transportation distances and costs in CLSCs. They reveal that increased reverse supply chain distances can decrease the optimal rate of remanufacturing (Pourjavad & Mayorga, 2019; Ullah, 2023). Further research has utilized collaborative frameworks and hybrid models to address sustainability, optimizing costs, environmental impacts, and social benefits within CLSC networks (Ramanathan et al., 2023). These insights underscore the complex interdependencies and innovation potential in managing CLSCs effectively.

In effect, the model can raise job opportunities and sustainable supplier purchases. In recent years, many models of CLSCN have been proposed concerning various aspects (Atabaki et al., 2019; Attia et al., 2020; De Angelis et al., 2018; Keshavarz-Ghorbani & Pasandideh, 2023; Motevalli-Taher et al., 2020). Salehi-Amiri et al. (2022) proposed a bi-objective model for the avocado industry, emphasizing cost minimization and job creation. Soleimani et al. (2022) designed a sustainable CLSC prioritizing energy efficiency, demonstrating the effectiveness of their algorithms in managing complex supply chain configurations. Similarly, Tavana et al. (2022) developed a multi-objective mixed-integer linear programming (MOMILP) model aimed at reducing costs, minimizing environmental impact, and enhancing social benefits through job opportunities. Their approach integrated supplier selection, order allocation, transportation planning, simulation application algorithms, and goal programming to address uncertainties in the supply chain. These studies collectively highlight the shift towards integrating diverse goals within CLSC frameworks to achieve sustainability.

Atabaki et al. (2020) explored new robust optimization models to redesign CLSC networks for durable products with an emphasis on minimizing costs, CO_2 emissions, and energy consumption. Their findings underscored the superiority of circular supply chains as well as the robustness of their models against uncertainty by employing methodologies such as mixed-integer linear programming, possibilistic programming, and scenario-based stochastic programming. Similarly, Gholipour et al. (2023) targeted the optimization of a sustainable CLSC, specifically for pomegranates, leveraging artificial intelligence in waste recycling to enhance both economic and environmental outcomes. This study, along with others like Rahbari et al. (2023a) who employed multi-objective robust fuzzy stochastic programming for agri-food supply chains, reflects a growing trend toward addressing sustainability under conditions of uncertainty with significant impacts on cost management and customer satisfaction. On a more specific product basis, studies like those by Kazemi et al. (2021) and Keshavarz-Ghorbani and Pasandideh (2022) have formulated bi-objective models to address both economic and environmental impacts within their respective supply chains for rice and agricultural products. These studies emphasized the importance of environmental considerations and demonstrated practical resilience against uncertainties. In addition, the work by Ade Irawan et al. (2022) employed a metaheuristic algorithm to optimize bi-objective sustainable closed-loop supply chain networks, focusing on minimizing logistic costs and carbon emissions and highlighted the stability of supply chain configurations in response to customer demand fluctuations.

Babaveisi et al. (2018b) explored a multi-objective approach for CLSCs, employing NSGA-II, MOSA, and MOPSO algorithms to maximize profit, minimize risks, and reduce product shortages. Their study highlighted the efficiency of NSGA-II in initial solutions, which were then validated and enhanced through MOSA and MOPSO, demonstrating the importance of priority-based encoding and parameter tuning through the Taguchi method for optimizing performance across various metrics. Similarly, Fathollahi-Fard et al. (2018) introduced a multi-objective stochastic CLSC network design incorporating social considerations, where new hybrid metaheuristic algorithms were tuned to better interact during search phases. This design illustrates significant improvements in existing methods of handling economic and social aspects simultaneously.

Agahgolnezhad Gerdrodbari et al. (2021) focused on optimizing perishable item supply chains by addressing economic and environmental concerns through a bi-objective model, emphasizing the critical role of demand sensitivity. Zarei-Kordshouli et al. (2023) developed a multistage decision-making framework for a sustainable diary supply chain. Similarly, Varas et al. (2020) introduced a multi-objective approach to support wine grape harvest operations, which balanced cost minimization with quality maximization and included a negotiation protocol that utilized an iterative Pareto solution process for decision-making. This theme of balancing competing objectives continued with Hasani et al. (2021), who designed a green, resilient global supply chain network using a hybrid heuristic method that integrated a strength Pareto evolutionary algorithm, demonstrating the network's agility and green capabilities while also pointing out the contradictions in current mitigation strategies. Further extending the theme of sustainability, Soori et al. (2022) explored the mushroom industry by developing a sustainable multi-objective agri-food supply chain that showed how increased capacity and pricing strategies could lead to significant economic and social improvements. Meanwhile, Gharye Mirzaei et al. (2022) investigated a dual-channel network in a sustainable closed-loop supply chain for rice, employing a mixed-integer linear programming approach alongside multi-objective metaheuristic algorithms.

A Stackelberg game model of centralized decision-making and decentralized decision-making is presented by Jian et al. (2021) according to a green closed-supply chain, including a manufacturer and retailer. The decision-making of supply chain members is considered, and significant results are given. Furthermore, a CLSC optimization problem is solved in the study for a perishable agricultural product, and three pillars of sustainability are obtained. The total network cost is reduced, carbon dioxide emission is minimized, and responsiveness to demand is increased. Furthermore, an innovative mixed-integer nonlinear programming model is extended by Hajiaghaei-Keshteli and Fathollahi Fard (2019) to formulate a multi-objective sustainable CLSCN. The presented model optimizes the total cost and environmental issues of building the utilities. Circular supply chains (CSCs), which perform better in terms of sustainability, are replacing traditional supply chains as the circular economy (CE) takes hold. Other related studies are also summarized in Table I.

Considering the reviewed papers, there are some significant limitations. One limitation is that it is rare to find a study that considers all levels of the supply chain in a closed-loop model. Another limitation is that the reviewed articles give less attention to discussing the social aspect rather than other aspects of sustainability. An important point in these studies is that the models in this area were mainly NP-hard. The metaheuristic and heuristic methods were recommended for more accurate and larger solutions. To illuminate this uncharted territory, the current paper presents a closed-loop sustainable supply chain model considering all levels of the supply chain. More attention is given to the social dimension of sustainability. This model is solved with multi-objective and Pareto front methods. Concerning environmental issues, energy consumption is selected as the objective function in this model.

Table I. Summary of various sustainable CLSC models based on previous studies

Study	Number of objectives	Number of products	Supply chain		Cost	Social		Environment		Vehicles fleet		Model		Method
			F	CL		JO	WT	PI	EC	HT	HM	Certain	Uncertain	
Pasandideh et al. (2015**)**	Bi obj	M	*	-	*	-	-	-	-	-	*	-	*	NSGA-II Non-dominated Ranking Genetic Algorithm (NRGA)
Babaveisi et al. (2018b**)**	M obj	M	-	*	*	-	-	-	-	-	*	*	-	NSGA-II MOPSO MOSA
Fathollahi-Fard et al. (2018)	M obj	S	-	*	*	*	-	-	-	-	*	-	*	NSGA-II Red Deer Algorithm (RDA) Keshtel Algorithm (KA)
Hajiaghaei-Keshteli & Fathollahi Fard (2019)	M obj	S	-	*	*	*	-	*	-	-	*	*	-	RDA GA KAGA
Yavari & Geraeli (2019)	Bi obj	M	-	*	*	-	-	*	-	-	*	-	*	Yavari and Geraeli Method (YAG)
Govindan et al. (2020)	Bi obj	M	-	*	*	-	-	*	-	*	-	-	*	Fuzzy DEMATEL Fuzzy ANP
Atabaki et al. (2020)	M obj	S	-	*	*	-	-	*	*	*	-	-	*	ε-constraint
Motevalli-Taher et al. (2020)	M obj	M	*	-	*	*	-	-	*	-	*	-	*	Meta-goal Programming
Yun et al. (2020)	M obj	S	-	*	*	*	-	*	-	-	*	*	-	GA
Agahgolnezhad Gerdrodbari et al. (2021)	M obj	S	-	*	*	-	-	*	-	-	*	*	-	ε-constraint
Hasani et al. (2021)	M obj	M	*	-	*	-	-	*	-	*	-	-	*	Strength Pareto Evolutionary Algorithm 2 (SPEA2)
Ade Irawan et al. (2022)	Bi obj	S	*	-	*	-	-	*	-	*	-	*	-	Metaheuristic
Soori et al. (2022)	M obj	M	*	-	*	*	-	*	-	-	*	-	*	ε-constraint
Gharye Mirzaei et al. (2022)	M obj	S	-	*	*	*	-	*	-	-	*	-	*	MOPSO Multi-Objective Simulated Annealing (MOSA)
Gholipour et al. (2023)	M obj	S	-	*	*	-	-	*	-	-	*	*	-	MOPSO NSGA-II
Kazemi et al. (2021)	Bi obj	M	*	-	*	-	-	*	-	-	*	-	*	Extended Goal Programming
Varas et al. (2020)	Bi obj	M	*	-	*	*	-	-	-	-	-	*	-	Augmented ε-constraint
Rahbari et al. (2023a)	M obj	M	*	-	*	*	-	*	-	*	-	-	*	GAMS
Keshavarz-Ghorbani & Pasandideh (2022)	Bi obj	M	*	-	*	-	-	*	-	*	-	-	*	ε-constraint Lagrangian relaxation
Keshavarz-Ghorbani & Pasandideh (2023)	Bi obj	M	-	*	*	*	-	-	-	-	*	*	-	ε-constraint
Rahbari et al. (2024**)**	S obj	M	*	*	*	-	-	-	-	*	-	-	*	GAMS
Current Study	M obj	S	-	*	*	*	*	-	*	*	-	*	-	NSGA-II MOPSO

F: forward, CL: closed-loop, JO: job opportunities, WT: worker training,
PI: pollution impact, EC: energy consumption, HT: heterogeneous, HM: homogeneous, M: multi, S: single.

III. PROBLEM DEFINITIONS, ASSUMPTIONS AND MATHEMATICAL FORMULATIONS

While there are many approaches and methods in the literature to address systemic problems (Deb et al., 2002; Khazaei et al., 2021; Ramezani et al., 2021; Shayannia, 2023), this study presents models for both direct and reverse supply chains, examining all levels involved (Atabaki et al., 2019; Gharye Mirzaei et al., 2022; Hajiaghaei-Keshteli & Fathollahi Fard, 2019; Tavana et al., 2022). In the direct supply chain, the study focuses on supplier selection, manufacturing setup, technology, transportation optimization, and consumer delivery. Conversely, the reverse supply chain addresses the planning of necessary facilities, transportation, and decisions concerning returned products. Returned and end-of-life products are collected and sent to disassembly centers, where they are categorized based on quality into three streams: reuse in production, sale in recycled materials markets, and disposal. The study also introduces a CLSC model that integrates both flows, featuring facilities like production, distribution, collection, refurbishment, recycling, and disposal centers. *Fig. 1* shows a schematic diagram of the study. This model illustrates the flow of materials and parts from production to customer and then back through the supply chain after product's end-of-life. The study emphasizes the need for sustainability in supply chain design, incorporating economic, environmental, and social dimensions, with a particular focus on reducing energy consumption, minimizing costs, and enhancing social impacts through job creation and training. Despite its comprehensive approach, the social sustainability aspect has been less explored in previous research. The model assumptions are as follows:

- Only one product is produced in the supply chain network.
- The production planning considered in this research includes a single period.
- There is no discount or late penalty in the supply chain.
- Apart from the location of suppliers and customers, which is fixed, potential deployment locations have been identified for the rest of the facilities.
- Collection centers must collect all returned products.
- The maximum number and capacity of the built facilities has been determined.
- At most, one technology should be selected in each production center.
- Different types of vehicles can be chosen between different levels of the supply chain.

Table II presents the mathematical model's indices and variables.

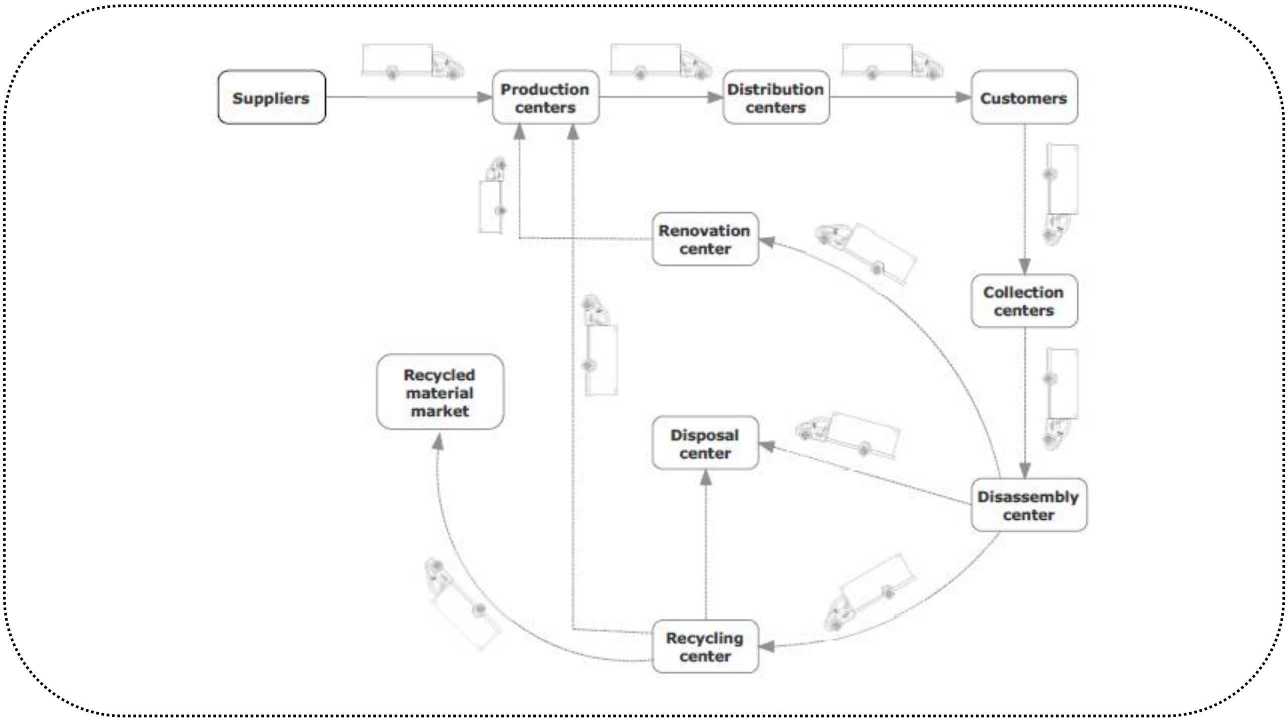


Fig. 1. Schematic diagram of the CLSC

Table II. Index list of the mathematical model

Indices:	
M	raw material set as each represented by m
P	part set as each represented by p
S	supplier set as each represented by s
I	potential production center set as each represented by i
J	potential distribution center set as each represented by j
G	customer set as each represented by g
H	potential collection center set as each represented by h
R	potential material recycling center set as each represented by r
D	potential disposal center set as each represented by d
N	potential renovation center set as each represented by n
Z	recycled material market set as each represented by z
T	potential disassembly center set as each represented by t
V	transportation type set as each represented by v
q	production technology set as each represented by q
Parameters:	
Cm_{ms}	cost of buying 1 kg of material m from supplier s
cp_{ps}	cost of buying 1 unit of part p from supplier s
pm_m	the price of 1 kg of material m in recycled material market
ci_{qi}	the cost of producing 1 unit of product in the production center i with technology q
cj_j	the cost of shipping 1 unit of product in the distribution center j
ch_h	processing cost of 1 unit of returned product at the collection center h
cr_{mr}	the cost of processing 1 kg of material m at the recycling center r
cn_{pn}	the cost of processing 1 unit of part p at the renovation center n
ct_t	the cost of processing 1 unit of returned product at the disassemble center t
cd_{md}	the cost of safe disposal of 1 kg of raw material m in the disposal center d
fi_{qi}	fixed cost of construction of production center i with technology q
fU_u	fixed cost of construction of facility U
cap_{sp}	the capacity of supplier s to supply part p
cas_{sm}	capacity of supplier s to supply raw material m
cai_{qi}	the capacity of product center i with technology q
caj_j	the capacity of distribution center j
cah_h	the capacity of collection center h
car_{rm}	the capacity of recycling center r to recycle raw material m
cad_{dm}	the capacity of disposal center d for raw material m
can_{np}	the capacity of renovation center n for part p
de_g	demand of customer g

Continue Table II. Index list of the mathematical model

re_g	returned product number from customer *g*
α_m	volume of raw material *m* in 1 unit of the product
ε_m	the usable rate of recycled material *m*
β_p	the coefficient of consumption of part *p* in 1 unit of the product
ρ_m	the unusable rate of raw material *m* after recycling
φ_p	renewal rate of part *p* after disassembling
ψ_p	recoverable rate of part *p* after product disassembly
λ_{mp}	the volume of raw material m in part *p*
ci_{iq}	the cost of producing 1 unit of the product in assembly center *i* with technology *q*
ct_t	processing cost of returned product at disassembly center *t*
cv_v	the cost of movement of 1 km by vehicle *v*
dUX	distance between facility *U* and *X*
U^{max}	maximum number of facility *U* that can be built
vv_v	the capacity of the vehicle *v* to carry the product
vm_{vm}	the capacity of the vehicle *v* to carry raw material *m*
vp_{vp}	the capacity of the vehicle *v* to carry part *p*
Cai_{qi}	the capacity of production center *i* with technology *q*
Mm_{mz}	demand for raw material m in recycled material market *z*
ei_{qi}	energy consumed to produce 1 unit of the product in production center i with technology *q*
em_{ms}	energy consumed to produce raw material *m* in the supplier *s*
ep_{ps}	energy consumed to produce part *p* in the supplier s
eu_u	energy consumed in processing 1 unit of the product in the facility center *u*
et_v	energy consumed in movement of 1 km by vehicle type *v*
eni_{qi}	energy consumed to build production center *i* with technology *q*
$enUu$	energy consumed to build facility *U*
$TTrc$	the total expected cost of workers' training in the supply chain
Trc_i	workers' training cost in the production center *i*
Trc_u	workers' training cost in the facility center *u*
Nfj_i	the number of fixed job opportunities created in the production center *i*
Nfj_u	the number of fixed job opportunities created in the facility center *u*
Nvj_s	the minimum number of operational workers required at supplier center *s*
Nvj_u	the minimum number of operational workers required at facility center *u*
Qs	the number of products that an operational worker can produce at supplier center *s*
Qi	the number of products that an operational worker can produce at production center *i*
Qr	the number of products that an operational worker can recycle at recycling center *r*
Qn	the number of products that an operational worker can renovate at renovation center *n*
Qt	the number of products that an operational worker can disassemble at disassembly center *t*

Continue Table II. Index list of the mathematical model

Non-negative continuous variables:	
XUX_{mux}	the amount of raw material m transferred from the facility center u to facility center *x*
XUX_{pux}	the amount of part *p* transferred from the facility center u to the facility center *x*
XIJ_{qij}	the amount of the product transferred from the production center *i* with technology *q* to distribution center *j*
XJG_{jg}	the amount of the product transferred from the distribution center *j* to the customer *g*
XGH_{gh}	the amount of the returned product transferred from the customer g to collection center *h*
XHT_{ht}	the amount of the returned product transferred from the collection center *h* to disassembly center *t*
Integer variables:	
VPI_{pvsi}	vehicle type *v* number to transfer the part p from the supplier s to the production center *i*
VMI_{mvsi}	vehicle type v number to transfer raw material m from the supplier *s* to the center *i*
VUX_{vux}	vehicle type *v* number to transfer product / returned product from the facility center u to facility center *x*
VUX_{pvux}	vehicle type *v* number to transfer part *p* from the facility center *u* to facility center *x*
VUX_{mvux}	vehicle type *v* number to transfer raw material m from the facility center *u* to facility center *x*
W_s	the number of employed workers in the supplier s
W_u	the number of employed workers in the facility center *u*
Binary variables:	
YI_{qi}	if the production center i with technology *q* is built *YI* is equal to one. Otherwise, *YI* is equal to zero.
YU_u	if the facility *U* is built *YU* is equal to one. Otherwise, *YU* is equal to zero.

A. Mathematical model objective functions

In this research, the sustainable CLSCD problem is defined by the MILP model that considers three objective functions including economic, environmental, and social. The economic objective is developed to minimize network cost; the environmental objective is developed to minimize consumed energy in the supply chain; and the social aspect is developed to maximize job opportunities in the system and train employed workers. The first objective function presents an economic aspect of sustainability, equation 1, which is used to minimize cost, has 5 sections as follows : (1) equation 2 presents network facilities establishment cost, for both direct (production and distribution centers) and reverse (collection, disassembling, recycling, renovation and disposal centers) supply chain, (2) equation 3 presents purchasing cost of raw materials and parts in the network, which also shows the income from the sale of recycled materials in the relevant market, (3) equation 4 introduces the operational cost of each facility in both forward and reverse SCs such as production, distribution, collection, disassembling, recycling, renovation, and disposal costs, (4) equation 5 points to network distribution cost, and (5) equation 6 indicates education and training cost of operational employed workers in the facilities.

$$Min\ Obj1 = Obj1^{Est} + Obj1^{Pcu} + Obj1^{Pro} + Obj1^{Tra} + Obj1^{Trc} \tag{1}$$

$$Obj1^{Est} = \sum_{i\in I}\sum_{q\in Q} fi_{qi}YI_{qi} + \sum_{j\in J} fj_jYJ_j + \sum_{h\in H} fh_hYH_h + \sum_{t\in T} ft_tYT_t + \sum_{r\in R} fr_rYR_r + \sum_{d\in D} fd_dYD_d + \sum_{n\in N} fn_nYN_n \tag{2}$$

$$Obj\ 1^{Pcu} = \sum_{m\in M}\sum_{s\in S}\sum_{i\in I} cm_{ms}XMI_{msi} + \sum_{p\in P}\sum_{s\in S}\sum_{i\in I} cp_{ps}XPI_{psi} - \sum_{m\in M}\sum_{r\in R}\sum_{z\in Z} pm_m XRZ_{mrz} \tag{3}$$

$$\begin{aligned} Obj\ 1^{Pro} = &\sum_{i\in I}\sum_{j\in J} ci_{qi}XIJ_{qij} + \sum_{j\in J}\sum_{g\in G} cj_j XJG_{jg} + \sum_{h\in H}\sum_{t\in T} ch_h XHT_{ht} + \sum_{h\in H}\sum_{t\in T} ct_t XHT_{ht} \\ &+ \sum_{m\in M}\sum_{p\in P}\sum_{t\in T}\sum_{r\in R} cr_{mr}\left(\lambda_{mp}XTR_{ptr}\right) + \sum_{p\in P}\sum_{t\in T}\sum_{n\in N} cn_{pn}XTN_{ptn} + \sum_{m\in M}\sum_{r\in R}\sum_{d\in D} cd_{md}XRD_{mrd} \\ &+ \sum_{m\in M}\sum_{p\in P}\sum_{t\in T}\sum_{d\in D} cd_{md}\lambda_{mp}XTD_{ptd} \end{aligned} \tag{4}$$

$$\begin{aligned} Obj1^{Tra} = &\sum_{m\in M}\sum_{v\in V}\sum_{s\in S}\sum_{i\in I} cv_v dsi_{si}VMI_{mvsi} + \sum_{p\in p}\sum_{v\in V}\sum_{s\in S}\sum_{i\in I} cv_v dsi_{si}VPI_{pvsi} + \sum_{v\in V}\sum_{i\in I}\sum_{j\in J} cv_v dij_{ij}VIJ_{vij} \\ &+ \sum_{v\in V}\sum_{j\in J}\sum_{g\in G} cv_v djg_{jg}VJG_{vjg} + \sum_{v\in V}\sum_{g\in G}\sum_{h\in H} cv_v dgh_{gh}VGH_{vgh} + \sum_{v\in V}\sum_{h\in H}\sum_{t\in T} cv_v dht_{ht}VHT_{vht} \\ &+ \sum_{p\in P}\sum_{v\in V}\sum_{t\in T}\sum_{r\in R} cv_v dtr_{tr}VPR_{pvtr} + \sum_{p\in P}\sum_{v\in V}\sum_{t\in T}\sum_{d\in D} cv_v dtd_{td}VPD_{pvtd} \\ &+ \sum_{p\in P}\sum_{v\in V}\sum_{t\in T}\sum_{n\in N} cv_v dtn_{tn}VPN_{pvtn} + \sum_{m\in M}\sum_{v\in V}\sum_{r\in R}\sum_{d\in D} cv_v drd_{rd}VRD_{mvrd} \\ &+ \sum_{m\in M}\sum_{v\in V}\sum_{r\in R}\sum_{z\in Z} cv_v drz_{rz}VMZ_{mvrz} + \sum_{m\in M}\sum_{v\in V}\sum_{r\in R}\sum_{i\in I} cv_v dri_{ri}VRI_{mvri} \\ &+ \sum_{p\in P}\sum_{v\in V}\sum_{n\in N}\sum_{i\in I} cv_v dni_{ni}VNI_{pvni} \end{aligned} \tag{5}$$

$$Obj1^{Trc} = \left(\sum_{i\in I} w_i * Trc_i + \sum_{r\in R} w_r * Trc_r + \sum_{n\in N} w_n * Trc_n + \sum_{t\in T} w_t * Trc_t\right) \tag{6}$$

The second objective function, equation 7, minimizes energy consumption which refers to the environmental aspect of sustainability and includes four sections: (1) equation 8 presents energy consumption during facility establishment, (2) equation 9 points to suppliers' energy usage to produce raw materials and parts that are needed for network production centers, (3) equation 10 indicates energy consumed for operational and processing works, and (4) equation 11 calculates the energy consumption due to the transportation of products, raw materials and parts in both direct and reverse flow.

$$Min\ Obj2 = Obj2^{Est} + Obj2^{Pcu} + Obj2^{Pro} + Obj2^{Tra} \tag{7}$$

$$\begin{aligned} Obj2^{Est} = &\sum_{i\in I} eni_{qi}YI_{qi} + \sum_{j\in J} enj_j YJ_j + \sum_{h\in H} enh_h YH_h + \sum_{t\in T} ent_t YT_t + \sum_{r\in R} enr_r YR_r + \sum_{d\in D} end_d YD_d \\ &+ \sum_{n\in N} enn_n YN_n \end{aligned} \tag{8}$$

$$Obj2^{Pcu} = \sum_{m\in M}\sum_{s\in S}\sum_{i\in I} em_{ms}XMI_{msi} + \sum_{p\in P}\sum_{s\in S}\sum_{i\in I} ep_{ps}XPI_{psi} \tag{9}$$

$$
\begin{aligned}
Obj\ 2^{Pro} = & \sum_{i\in I}\sum_{j\in J} ei_{qi}XIJ_{qij} + \sum_{j\in J}\sum_{g\in G} ej_j XJG_{jg} + \sum_{h\in H}\sum_{t\in T} eh_h XHT_{ht} + \sum_{h\in H}\sum_{t\in T} et_t XHT_{ht} \\
& + \sum_{m\in M}\sum_{p\in P}\sum_{t\in T}\sum_{r\in R} er_{mr}\left(\lambda_{mp} XTR_{ptr}\right) + \sum_{p\in P}\sum_{t\in T}\sum_{n\in N} en_{pn} XTN_{ptn} \\
& + \sum_{m\in M}\sum_{p\in P}\sum_{r\in R}\sum_{t\in T}\sum_{d\in D} ed_{md}\left(\lambda_{mp} XTD_{ptd} + XRD_{mrd}\right)
\end{aligned} \tag{10}
$$

$$
\begin{aligned}
Obj2^{Tra} = & \sum_{m\in M}\sum_{v\in V}\sum_{s\in S}\sum_{i\in I} et_v dsi_{si} VMI_{mvsi} + \sum_{p\in P}\sum_{v\in V}\sum_{s\in S}\sum_{i\in I} et_v dsi_{si} VPI_{pvsi} + \sum_{v\in V}\sum_{i\in I}\sum_{j\in J} et_v dij_{ij} VIJ_{vij} \\
& + \sum_{v\in V}\sum_{j\in J}\sum_{g\in G} et_v djg_{jg} VJG_{vjg} + \sum_{v\in V}\sum_{g\in G}\sum_{h\in H} et_v dgh_{gh} VGH_{vgh} + \sum_{v\in V}\sum_{h\in H}\sum_{t\in T} et_v dht_{ht} VHT_{vht} \\
& + \sum_{p\in P}\sum_{v\in V}\sum_{t\in T}\sum_{r\in R} et_v dtr_{tr} VPR_{pvtr} + \sum_{p\in P}\sum_{v\in V}\sum_{t\in T}\sum_{d\in D} et_v dtd_{td} VPD_{pvtd} \\
& + \sum_{p\in P}\sum_{v\in V}\sum_{t\in T}\sum_{n\in N} et_v dtn_{tn} VPN_{pvtn} + \sum_{m\in M}\sum_{v\in V}\sum_{r\in R}\sum_{d\in D} et_v drd_{rd} VRD_{mvrd} \\
& + \sum_{m\in M}\sum_{v\in V}\sum_{r\in R}\sum_{z\in Z} et_v drz_{rz} VMZ_{mvrz} + \sum_{m\in M}\sum_{v\in V}\sum_{r\in R}\sum_{i\in I} et_v dri_{ri} VRI_{mvri} \\
& + \sum_{p\in P}\sum_{v\in V}\sum_{n\in N}\sum_{i\in I} et_v dni_{ni} VNI_{pvni}
\end{aligned} \tag{11}
$$

The third objective function is about the social aspect of sustainability and maximizes both fixed and variable job opportunities in the supply chain.

$$
\begin{aligned}
Max\ obj\ 3 = & \left\{\sum_{i\in I} Nfj_i . YI_i + \sum_{r\in R} Nfj_r . YR_r + \sum_{n\in N} NFJ_n . YN_n + \sum_{t\in T} Nfj_t . YT_t\right\} + \sum_{s\in S} NVJ_s . Q_s . {}^{W_s}\!/_{Cap_s} \\
& + \sum_{i\in I} NVJ_i . Q_i . {}^{W_i}\!/_{cai_i} + \sum_{r\in R}\sum_{m\in M} NVJ_r . Q_r . {}^{W_r}\!/_{Car_{rm}} + \sum_{n\in N}\sum_{p\in P} NVJ_n . Q_n . {}^{W_n}\!/_{Can_{np}} \\
& + \sum_{t\in T}\sum_{m\in M} NVJ_t . Q_t . {}^{W_t}\!/_{Cat_{tm}}
\end{aligned} \tag{12}
$$

B. Model constraints

This study considers many constraints to ensure modeling the problem concerning real-world constraints. Equation 13 guarantees that the customers' demands are met through the distribution centers. Equation 14 ensures that the demands of all distribution centers are satisfied by production centers, where different technologies can be applied in the network. Equation 15 presents that a maximum amount of one kind of technology must be used in production centers.

$$\sum_{j\in J} XJG_{jg} \geq d_g \quad \forall g \tag{13}$$

$$\sum_{i\in I}\sum_{q\in Q} XIJ_{qij} \geq \sum_{g\in G} XJG_{jg} \quad \forall J \tag{14}$$

$$\sum_{q\in Q} YI_{qi} \leq 1 \quad \forall i \tag{15}$$

Equation 16 states that all raw materials needed at production centers to produce final products must be supplied from selected suppliers. Equation 17 indicates that all needed parts for production in manufacturing centers must be satisfied by suppliers in this supply chain.

$$\sum_{r\in R} XRI_{mri} + \sum_{s\in S} XMI_{msi} \geq \alpha_m \sum_{j\in J}\sum_{q\in Q} XIJ_{qij} \qquad \forall m,i \tag{16}$$

$$\sum_{n\in N} XNI_{pni} + \sum_{s\in S} XPI_{psi} \geq \beta_p \sum_{j\in J}\sum_{q\in Q} XIJ_{qij} \qquad \forall p,i \tag{17}$$

Equation 18 ensures that all customer-returned products must be collected by collection centers. All collected products must be sent to disassembly centers, which is represented by Equation 19. Equation 20 shows the maximum number of usable disassembled parts from returned products that can be sent from disassembly centers to renovation centers. Equation 21 indicates the maximum number of disassembled parts from returned products based on their quality, that can be transported from disassembly centers to recycling centers. Unusable parts that cannot be returned to the production cycle are sent to disposal centers, which are represented by Equation 22.

$$\sum_{h\in H} XGH_{gh} = re_g \qquad \forall g \tag{18}$$

$$\sum_{t\in T} XHT_{ht} = \sum_{g\in G} XGH_{gh} \qquad \forall h \tag{19}$$

$$\sum_{n\in N} XTN_{ptn} \leq \beta_p \varphi_p \sum_{h\in H} XHT_{ht} \qquad \forall t,p \tag{20}$$

$$\sum_{r\in R} XTR_{ptr} \leq \psi_p \beta_p \sum_{h\in H} XHT_{ht} \qquad \forall t,p \tag{21}$$

$$\sum_{d\in D} XTD_{ptd} \geq (1-\varphi_p-\psi_p)\beta_p \sum_{h\in H} XHT_{ht} \qquad \forall t,p \tag{22}$$

Equation 23 states that recycled materials in recycling centers can be transported to production centers or recycled material markets. Equation 24 guarantees that the unusable output of recycling processes will be moved to safe disposal centers. Equation 25 specifies that renovated parts in renovation centers will be sent to production and manufacturing centers. Equation 26 determines that recycling centers will not send materials to recycled material markets more than their capacity.

$$\sum_{i\in I} XRI_{mri} + \sum_{z\in Z} XRZ_{mrz} = \left(\sum_{t\in T}\sum_{p\in P} \lambda_{mp} XTR_{ptr}\right)(1-\rho_m) \qquad \forall m,r \tag{23}$$

$$\sum_{d\in D} XRD_{mrd} = \rho_m \left(\sum_{t\in T}\sum_{p\in P} \lambda_{mp} XTR_{ptr}\right) \qquad \forall m,r \tag{24}$$

$$\sum_{i\in I} XNI_{pni} = \sum_{t\in T} XTN_{ptn} \qquad \forall p,n \tag{25}$$

$$\sum_{r\in R} XRZ_{mrz} \leq mm_{mz} \qquad \forall m,z \tag{26}$$

One of the main goals of this model is to determine the number and type of vehicles used to transfer materials and products between facilities to minimize cost and optimize energy consumption. Equation 27 specifies the number and type of vehicles needed to move products from distribution centers to customers. Equation 28 determines the number and type of vehicles needed to move products from production centers to distribution centers. Equations 29 and 30 show the number and type of vehicles needed to move raw materials and parts from suppliers to production centers. Equations 31 through 39 specify transportation constraints to find the optimum number and type of vehicles that must be transported between facilities concerning the purpose of this model.

$$XJG_{jg} \leq \sum_{v \in V} vv_v VJG_{vjg} \quad \forall j, g \tag{27}$$

$$\sum_{q \in Q} XIJ_{qij} \leq \sum_{v \in V} vv_v VIJ_{vij} \quad \forall i, j \tag{28}$$

$$XMI_{msi} \leq \sum_{v \in V} vm_{vm} VMI_{mvsi} \quad \forall m, s, i \tag{29}$$

$$XPI_{psi} \leq \sum_{v \in V} vp_{vp} VPI_{pvsi} \quad \forall p, s, i \tag{30}$$

$$XGH_{gh} \leq \sum_{v \in V} vv_v VGH_{vgh} \quad \forall g, h \tag{31}$$

$$XHT_{ht} \leq \sum_{v \in V} vv_v VHT_{vht} \quad \forall h, t \tag{32}$$

$$XTN_{ptn} \leq \sum_{v \in V} vp_{vp} VPN_{pvtn} \quad \forall p, t, n \tag{33}$$

$$XTD_{ptd} \leq \sum_{v \in V} vp_{vp} VPD_{pvtd} \quad \forall p, t, d \tag{34}$$

$$XTR_{ptr} \leq \sum_{v \in V} vp_{vp} VPR_{pvtr} \quad \forall p, t, r \tag{35}$$

$$XRD_{mrd} \leq \sum_{v \in V} vm_{vm} VRD_{mvrd} \quad \forall m, r, d \tag{36}$$

$$XRI_{mri} \leq \sum_{v \in V} vm_{vm} VRI_{mvri} \quad \forall m, r, i \tag{37}$$

$$XRZ_{mrz} \leq \sum_{v \in V} vm_{vm} VMZ_{mvrz} \quad \forall m, r, z \tag{38}$$

$$XNI_{pni} \leq \sum_{v \in V} vp_{vp} VNI_{pvni} \quad \forall p, n, i \tag{39}$$

Limited capacity is assumed for all facilities in both the forward and reverse modes of this model. Equations 40 and 41 ensure that the volume of various raw materials and the number of parts sent from suppliers to production centers do not exceed the capacity of those suppliers. Equation 42 guarantees that the number of products produced in each production center does not exceed the capacity of that center. It also determines which production centers will be built and what kind of technology will be used in them. Equation 43 determines that the number of products distributed by each distribution center does not exceed the capacity of that center. This restriction also specifies which of the distribution centers should be built. Equations 44 through 48 represent the capacity limitations of the other mentioned facilities. These constraints ensure that the maximum amount of materials entering or exiting each facility does not exceed their capacity.

$$\sum_{i\in I} XMI_{msi} \leq cas_{sm} \quad \forall m, s \tag{40}$$

$$\sum_{i\in I} XPI_{psi} \leq cap_{sp} \quad \forall p, s \tag{41}$$

$$\sum_{j\in J} XIJ_{qij} \leq cai_{qi} YI_{qi} \quad \forall q, i \tag{42}$$

$$\sum_{g\in G} XJG_{jg} \leq caj_j YJ_j \quad \forall j \tag{43}$$

$$\sum_{g\in G} XGH_{gh} \leq cah_h YH_h \quad \forall h \tag{44}$$

$$\sum_{h\in H} XHT_{ht} \leq cat_t YT_t \quad \forall t \tag{45}$$

$$\sum_{p\in P}\sum_{t\in T} \lambda_{mp} XTR_{ptr} \leq car_{rm} YR_r \quad \forall m, r \tag{46}$$

$$\sum_{r\in R} XRD_{mrd} + \sum_{p\in P}\sum_{t\in T} \lambda_{mp} XTD_{ptd} \leq cad_{dm} YD_d \quad \forall m, d \tag{47}$$

$$\sum_{t\in T} XTN_{ptn} \leq can_{np} YN_n \quad \forall p, n \tag{48}$$

Equation 49 to equation 54 present the social aspect constraints. Equation 49 guarantees that workers' training costs in facilities should not exceed the considered amount by the network. Equation 50 to equation 54 state that the number of workers who should be employed in the mentioned facilities should not be less than the minimum number of workers requirement of this facility.

$$\sum_{i\in I} w_i * Trc_i + \sum_{r\in R} w_r * Trc_r + \sum_{n\in N} w_n * Trc_n + \sum_{t\in T} w_t * Trc_t \leq TTRc \tag{49}$$

$$\sum_{s\in S} w_s \geq NVJ_s \quad \forall\, S \tag{50}$$

$$\sum_{i\in I} w_i \geq NVJ_i \quad \forall\, I \tag{51}$$

$$\sum_{r\in R} w_r \geq NVJ_r \quad \forall\, R \tag{52}$$

$$\sum_{n \in N} w_n \geq NVJ_n \quad \forall N \tag{53}$$

$$\sum_{t \in T} w_t \geq NVJ_T \quad \forall T \tag{54}$$

Equation 55 to 61 show the maximum number of facilities that can be built in both the forward and reverse supply chains, including production (Eq.55), distribution (Eq.56), collection (Eq.57), disassembly (Eq.58), material recycling (Eq.59), renovation (Eq.60) and disposal (Eq.61) centers.

$$\sum_{i \in I} \sum_{q \in Q} YI_{qi} \leq i^{max} \tag{55}$$

$$\sum_{j \in J} YJ_j \leq j^{max} \tag{56}$$

$$\sum_{h \in H} YH_h \leq h^{max} \tag{57}$$

$$\sum_{t \in T} YT_t \leq t^{max} \tag{58}$$

$$\sum_{r \in R} YR_r \leq r^{max} \tag{59}$$

$$\sum_{n \in N} YN_n \leq n^{max} \tag{60}$$

$$\sum_{d \in D} YD_d \leq d^{max} \tag{61}$$

Equations 62 to 64 are related to the decision variables of the model.

$$\begin{gathered} XMI_{msi}, XPI_{Psi}, XJG_{jg}, XGH_{gh}, XHR_{phr}, XHN_{phn}, XRD_{mrd}, XRZ_{mrz}, XNI_{pni}, XIJ_{qij}, XGH_{gh}, \\ XHT_{ht}, XTR_{ptr}, XTD_{ptd}, XTN_{ptn}, XRI_{mri} \geq 0 \qquad \forall m, s, i, p, j, g, h, r, n, d, z, q, t \end{gathered} \tag{62}$$

$$\begin{gathered} VPI_{pvsi}, VMI_{mvsi}, VIJ_{vij}, VJG_{vjg}, VGH_{vgh}, VHT_{vht}, VPR_{pvtr}, VPD_{pvtd}, VPN_{pvtn}, VNI_{pvni}, VRD_{mvrd} \\ , VMZ_{mvrz}, VRI_{mvri}, W_s, W_i, W_r, W_n, W_t \geq 0 \;\&\; Integer \qquad \forall p, v, s, i, m, j, g, h, t, r, d, n, z \end{gathered} \tag{63}$$

$$YI_{qi}, YJ_j, YH_h, YT_t, YR_r, YN_n, YD_d \in \{0,1\} \qquad \forall q, i, j, h, t, r, n, d \tag{64}$$

IV. PROBLEM SOLUTION

The design of the CLSC is placed under the category of NP-hard problems due to its various dimensions. With precise solution methods, it is complicated to solve NP-hard problems, especially in medium and large sizes. Sometimes, it is not possible to solve these problems in a reasonable time (Alizadeh Afrouzy et al., 2018). Hence, metaheuristic methods are used to solve these problems. The set of Pareto front result solutions is more effective in helping decision-makers in the network. The conducted investigations have studied various metaheuristic solution methods in the field of supply chain, and as a result, two methods of NSGA-II and MOPSO have been found to be suitable and effective methods for solving supply chain design problems (Babaveisi et al., 2018b; Boskabadi et al., 2022).

To solve NP-hard optimization problems, the genetic algorithm is one of the most efficient metaheuristic solution methods (Ardakan et al., 2015). In recent years, many solving methods based on genetic algorithms have been developed, and NSGA-II is one of these developed methods. NSGA-II is a well-known method for solving multi-objective problems which is one of the most efficient multi-objective evolutionary algorithms (Juybari et al., 2022; Karimi et al., 2022). The high speed of this algorithm in moving towards finding the optimal point is one of the positive aspects of this solution method. Another feature that can be pointed out is that NSGA-II, unlike many other metaheuristic methods that search the feasible space of the problem in only one direction, performs a simultaneous search in several directions of the problem-solving space to find the global optimal solution. Another positive feature of NSGA-II is the "lack of continuity and convexity of the objective function" (Shayannia, 2023).

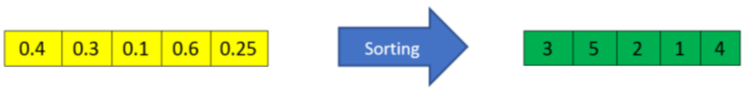
Another method used in this article is MOPSO. This method is efficient because it can solve models without considering assumptions or with few assumptions about the problem and to search for solutions in enormous spaces. Another positive feature of MOPSO is that, unlike many other solution methods, this algorithm "does not require that the optimization problem be differential" (Shayannia, 2023).

As a result, in this research, first NSGA-II is utilized to obtain results of the multi-objective problem, then MOPSO is used to confirm the validity of the obtained results.

A. Encoding and chromosome scheme

In this research, to obtain variables, random answers are considered between zero and one. Then by using techniques of sorting, normalization, and sometimes the other variables' solutions, the desired output variables are obtained. Also, due to the multiplicity of model levels, each random answer is analyzed separately.

Obtaining variables $XJG_{jg}, VJG_{vjg}, YJ_j$: first a random integer between 1 and j_{max} is created to obtain the number of variables of YJ_j that must be 1. Then, to find which j should be one, we separate the first row of the random answer's section one removes the discrete numbers using the sorting rule, and then separate the number of columns equal to the number of j. For example, if the random number is 3, then we separate row 1 from section 1, extract it using the rule of sorting discrete numbers, and finally separate 3 columns and get [3,5,2] which indicates this $YJ_3 = 1, YJ_5 = 1, YJ_2 = 1$.



For the sorting technique, suppose a matrix with the following random numbers is generated, and we want to extract discrete numbers from it:

0.3	0.9	0.6	0.1

Now, we sort them in ascending order using the sorting command as follows:

0.1	0.3	0.6	0.9

If we separate the first entry number with the sorting command, it will be a sequence of discrete numbers as follows:

4	1	3	2

For each g and with the knowledge of the variable YJ_J, using the parameter de_g and each row of g of the random answer, separate columns with YJ_J size, and finally, the value of XJG_{jg} is obtained by using the normalization rule. For example, if the first line of the random answer is as follows: [0.4,0.3,0.1,0.6,0.25], we separate three columns

[0.4,0.3,0.1], then normalize and multiply it by $de_g = 100$. That is: [0.5,0.125,0.375] *100= [50,12.5,37.5]

Finally, we get the variable VJG_{vjg} for each variable XJG_{jg} and parameter v_v in such a way that for each g, j:

First, the products to be sent are randomly selected. Then we generate random numbers between zero and one as many as the selected products. Next, by using the normalization rule, multiply it by a variable XJG_{jg}, and finally, obtain variable VJG_{vjg} by dividing it by the parameter v_v and rounding it. That is, for *j*=1, *g*=1, if the number of selected products is 2, then v2, and v3 products are selected. Then, we produce two random numbers between zero and one, normalize and multiply it by $XJG_{jg} = 50$: [0.4, 0.6] *50= [20,30]. Finally, we divide it by $v_v = [10,10]$, to get: $VJG_{211} = 2, VJG_{311} = 3$

	$\lvert G \rvert$		
	0.4	…	0.25
	…		…
	0.15	…	0.6
Random answer of part 1			

Obtaining the variables $XIJ_{qij}, VIJ_{vij}, YI_{qi}$: As in the first part, first, the number of *i* center is randomly determined based on the parameters of the model and the first line of the random answer, then the number and type of center *i* with technology q is determined randomly. After determining the number and type of *i*,*q*, the sent value of XIJ_{qij} should be obtained based on the constraint which is dependent on the variable XJG_{jg} (obtained from the previous step). Then, for each row j of the random answer and separating the columns with the size of q, *i* that was determined at the beginning, is separated, normalized, and multiplied by the variable $\sum_g XJG_{jg}$, as in part one, until the sent value of XIJ_{qij} is determined. It should be noted that the type of index q,i was obtained at the beginning, which should be included in each variable j. Now, the XIJ_{qij} variables are obtained as the first part, the VIJ_{vij} variable can be obtained only by changing the indices.

	$\lvert q \rvert + \lvert I \rvert$		
$\lvert j \rvert$	0.14	…	0.25
	…		…
	0.35	…	0.26
Random answer of part 2			

Obtaining the variables $XGH_{gh}, VGH_{vgh}, YH_h, XHT_{ht}, VHT_{vht}, YT_t$: In this section, the zero and one variable of YT_t, YH_h are determined by separating the first row and separating the columns of parts *H*, and *T* from the random solution and T_{max} parameters. Then, as in part one, the $XGH_{gh}, VGH_{vgh}, XHT_{ht}$, VHT_{vht} variables can be obtained, but the difference is in the type of indices and in separating process of the rows and columns. Also, the VHT_{vht} variables are obtained after the calculation of XGH_{gh} and the re_g parameter is used in the calculation of XGH_{gh}.

	$\lvert H \rvert + \lvert T \rvert$		
$\lvert G \rvert + \lvert H \rvert$	0.25	…	0.28
	…		…
	0.35	…	0.86
Random answer of part 3			

Similar to variables that have been decoded so far, the other variables of the problem are obtained based on the constraints, desired parameters, and the variables obtained from the previous steps.

B. NSGA-II

In the context of evolutionary multi-objective optimization, finding non-dominated solutions within evolutionary processes has been retained for different methods. Therefore, this sorting method in evolutionary multi-objective optimization algorithms has been enhanced over recent years. Initially, the non-dominated sorting strategy, proposed by Golberg (1989), was used as an efficient selection strategy in multi-objective optimization. Later, Srinivas and Deb (1994) applied the non-dominated sorting strategy in the genetic algorithm and proposed a non-dominated sorting genetic algorithm (NSGA) to solve the multi-objective optimization problems. Afterward, Deb et al. (2002) developed a more efficient non-dominated sorting strategy as an enhanced variant of NSGA known as fast non-dominated sort called NSGA-II. It is necessary to specify the value of the sharing parameter (σ share); the high computational complexity of non-dominated sorting and lack of elitism are the main criticisms of the NSGA approach, which have been solved in NSGA-II. This approach is one of the most efficient and robust evolutionary optimization algorithms for solving multi-objective optimization problems due to the effectiveness, simplicity, and optimization of user interaction provided in NSGA-II. Eventually, Table III shows the pseudocode of NSGA-II.

C. MOPSO

One of the popular methods for solving multi-objective problems in supply chain design, which has been used in many researches, is the MOPSO solution method (Javanshir et al., 2012). The MOPSO method is population-based. In this method, the initial population is randomly assigned, then this population moves into the feasible space of the problem to find a better solution. Each particle moves with a certain velocity in the problem-solving space to obtain a new solution set. In each iteration, this searching population is modified based on each particle's best local (Pbest) solution and the best global result (Gbest) obtained for all particles. Next, by calculating the distance of each particle of the new population from the Pbest and Gbest, the movement speed of each particle is determined. As each particle's search speed changes, these particles are updated in each iteration (Babaveisi et al., 2018a). Table IV shows the pseudocode of MOPSO.

Table III. The pseudocode of NSGA-II (Shehadeh et al., 2018)

```
Start
Population;    Initialize Population
Evaluate      Objective Functions (Population)
Fast Non-Dominated Sort (Population)
Sort              Select Parents by Rank
Offspring      Crossover and Mutation
While Stop Condition (number of generations) do
Evaluate Against Objective Functions (Offspring)
Union        Merge (Population, Offspring)
Fronts       Fast Non-Dominated Sort (Union)
For each Front do
Crowding Distance Assignment (Front)
If Size (Parents) + Size (Fronti) > POPsize then
Front       I:
Else
Parents       Merge (Parents, Front)
If Size (Parents) < POPsize then
Front       Sort by Rank and Distance (Front)
Selected        Select Parents by Rank and Distance (Parents,
POPsize);
Population       Offspring
Offspring         Crossover and Mutation (Selected, Pcrossover, Permutation)
          Return Offspring;
End
```

Table IV. The pseudocode of MOPSO (Shehadeh et al., 2018)

Start

1. Initial position for swarm and initials archives for leaders
2. Send leaders to archive
3. Generation(g)= 0
4. While g<g^{max} do
5. For each particle do
6. Leader selection
7. Update position
8. Mutation
9. Update the local best (Pbest)
10. EndFor
11. Update global leaders (gbest) in the archive
12. g=g+1
13. EndWhile
14. Back to archive and report results
15. End

V. COMPUTATIONAL RESULTS

This section first describes the data used to solve the mathematical model. In this section, the presented model is solved using two metaheuristic methods: NSGA-II and MOPSO. Then, the results are analyzed and interpreted.

To solve the presented model in this SCLSC design and analyze its performance, necessary data have been collected from the literature. To have a more effective and in-depth analysis of the efficiency of the model, a product that consists of four types of metal (nickel, steel, copper, and aluminum) is considered. The mentioned product is made directly from steel, nickel, and copper as raw materials as well as from parts that contain nickel and aluminum. The prices of these metals are extracted from the Shanghai Metal Market prices in 2017. Also, the amount of energy consumed in the production stage of raw materials for metals, parts, finished products, and other levels of the network has been obtained from the subject literature (Atabaki et al., 2020). The final price and the amount of energy consumed to produce these raw materials and parts will vary according to the production technology used as well as the quality and efficiency of each supplier. Hence, this research multiplies this data by a random number in the range of [1.1,1.4] to get closer to real-world conditions. More details about the used data are given in Tables V to VII.

A. Results

The presented mathematical model has been solved by using two methods, NSGA-II and MOPSO, in the MATLAB environment to reach the Pareto front solutions. The results of the objective functions are presented as a batch of answers so that decision-makers can choose the best policy based on different policies during different periods. Table VIII shows the set of optimal solutions obtained for cost, social, and environmental objective functions. Examining these results determines the conflict and misalignment of the functions. For example, if the cost in the network is reduced, more energy is consumed. In other words, the energy reduction causes the costs to rise. Two points of view are examined in examining the function of the social goal. With the increasing number of established facilities in the supply chain, the number of job opportunities created will be increased; at the same time, the costs of building the facilities and the social goal function will also rise. However, the sub-objective function of training employed workers, which is categorized under the cost objective function, solves the problem of an unreasonable increase in the employment of workers. This plays an essential role in maintaining balance.

Fig. 2 presents the Pareto Front image of the cost objective function versus energy consumption. *Figs 3* and *4* sequentially present the Pareto Front image of the cost objective function versus social factor and energy consumption versus social factor. *Fig. 5* shows a 3D Pareto Front image of all three objective functions versus each other simultaneously.

Table V. Required energy and cost to produce raw materials (Atabaki et al., 2020)

Raw material	Price ($/KG)	Required energy (MJ/KG)
Copper	2.2	57
Aluminum	7.2	218
Steel	12.2	35
Nickel	0.8	164

Table VI. Coefficient of consumption of raw materials in the manufacturing of parts (Atabaki et al., 2020)

Raw material	Parts		
	1	2	3
Steel	0	0	0
Copper	0	0	0
Nickel	1.5	2	1
Aluminum	1	1	1.5

Table VII. Required energy to recycle raw materials (Atabaki et al., 2020)

Raw material	Percentage of primary production
Copper	15%
Aluminum	5 to 10 %
Steel	20 to 40 %
Nickel	10%

Table VIII. NSGA-II sets of optimal solutions

NSGA-II	Cost objective	Energy consuming	Social objective
1	15864607.5119	6377103.1492	837
2	13565659.3232	6880590.5884	819
3	21804498.5948	7822605.67	932
4	19533906.9728	7979606.2914	934
5	17170370.1088	7406034.1187	929
6	15904829.2823	6798887.5804	882
7	18120665.895	6463930.8786	911
8	13761603.6885	7200072.9646	831
9	14447087.8937	7377400.9261	882
10	18532665.6001	8058828.2829	932
11	15088176.8997	7153624.0835	917
12	14351310.2843	7263663.8795	863
13	20540035.7922	7633940.5883	934
14	14367332.1174	6783589.2211	847
15	16736942.6042	6699361.7079	917

Continue Table VIII. NSGA-II sets of optimal solutions

NSGA-II	Cost objective	Energy consuming	Social objective
16	18830461.4905	7667971.8799	932
17	19102186.5616	7757262.6602	931
18	17286923.6431	6345928.8562	863
19	17443774.6106	6588527.734	921
20	20218762.9641	8043147.7984	932
21	16991807.9589	7610692.8562	928
22	18491852.4848	7893583.6153	931
23	17885696.6497	7627708.3003	929
24	16968419.7403	7602581.7086	926
25	18015695.4566	6503766.6946	929

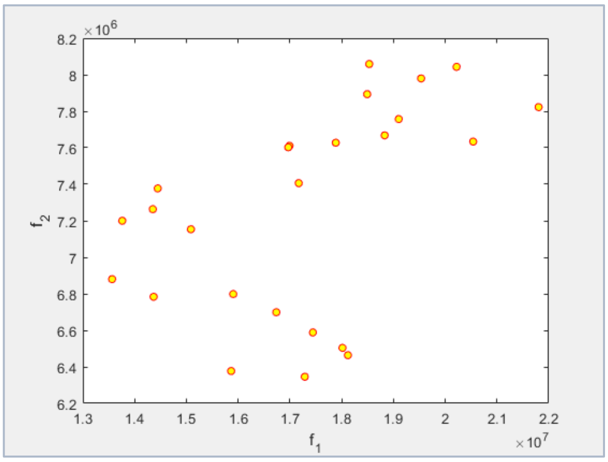


Fig. 2. Pareto front of cost objective function vs. energy consumption

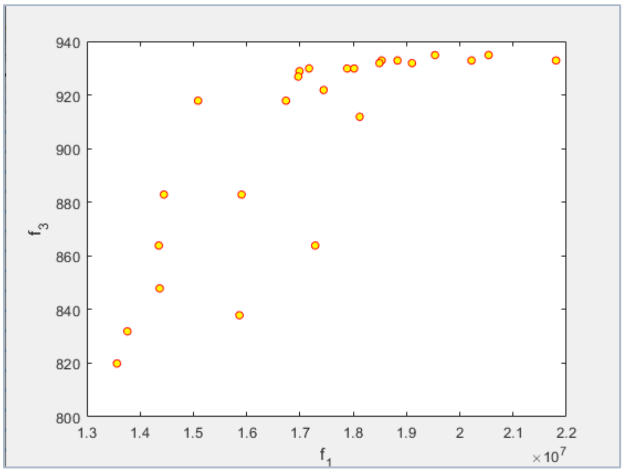


Fig. 3. Pareto front of cost objective function vs. social factor

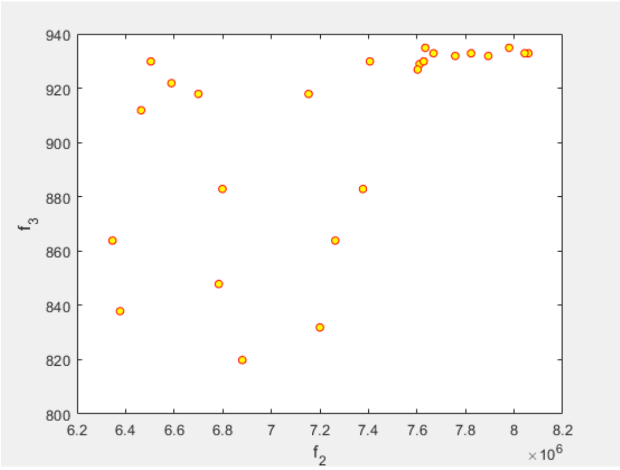


Fig. 4. Pareto front of energy consumption vs. social factor

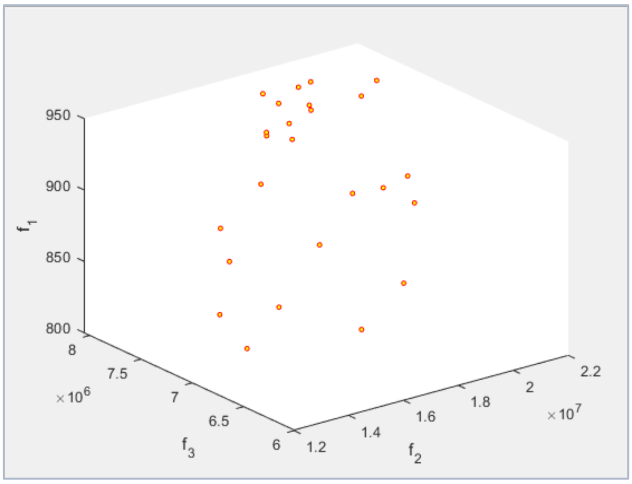


Fig. 5. Pareto front of objective 1 vs. objective 2 vs. objective 3

Table IX shows the set of optimal solutions for this mathematical model answers by using the MOPSO solution method. Table X shows the comparison of the most optimal solutions among all of the categories of the obtained solutions, that is, the minimum amount of cost and energy consumption and the maximum level of social factors in both solution methods. Using the results listed in this Table, we find that for solving a small-sized problem, NSGA-II provides better and more optimal answers for each objective function of this research for the decision-makers.

Fig. 6 shows the results obtained for the proposed objective function in the designed model. This figure presents two points. First, it shows which facility has been established according to the solving data of this problem and whether it is in the direct flow or the reverse flow network. A second important point that is interpreted from these results is how many operational workers should be employed in each of the operational units based on the capacity of the facility, the amount of existing demand, and the expected capabilities of the workers. For example, production centers have been established in four locations, and the number of workers employed in each unit is known. For this supply chain, concerning the ratio of returned products to demand, the ratio of parts with suitable quality for renovation, and the high capacity of renovation centers, only one renovation center needs to be established. In this center, employed workers have been shown as well.

Fig. 7 shows the number of manufacturing products and selected technology in each production center to satisfy the demand in the network. In addition, the exploitation percentage of each center to its capacity is obtained from these results, which helps managers in hiring decisions for the required workers.

Table IX. MOPSO sets of optimal solutions

MOPSO	Cost objective	Energy consuming	Social objective
1	18105515.7144	7494562.2545	931
2	18610777.8856	7661157.9752	930
3	20639032.2387	7360451.7442	918
4	19301549.8279	7351070.9566	913
5	17857031.5355	7433366.2113	909
6	16630180.5122	8427808.4911	896
7	15131004.8393	6757844.6136	890
8	14515828.7521	7529727.7086	856
9	13959472.9998	8204032.3103	798

Table X. NSGA-II and MOPSO best solutions

Method	The best solution for cost objective	The best solution for energy consuming	The best solution for social objective
NSGA-II	13565659.3232	6345928.8562	934
MOPSO	13959472.9998	6757844.6136	931

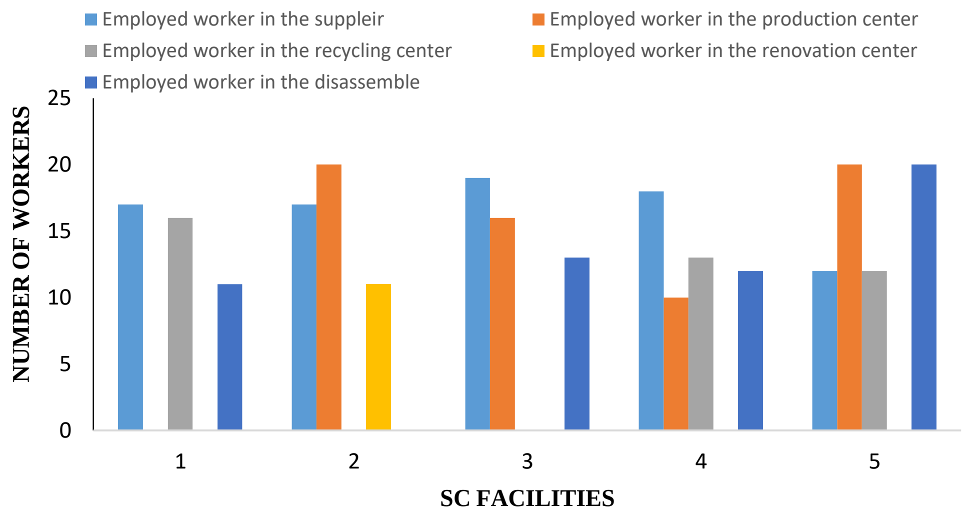


Fig. 6. Number of operational workers employed in the network

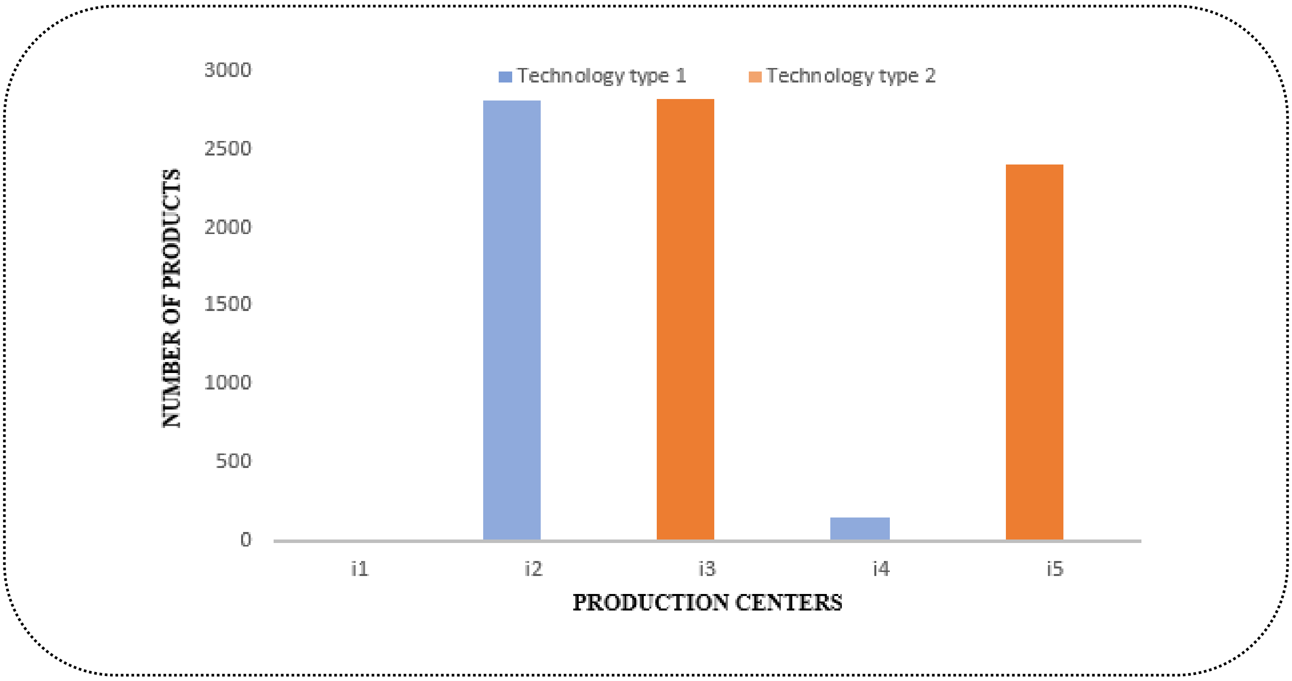


Fig. 7. Quantity of manufacturing products

Table XI presents the number and type of vehicles used in each network echelon to transport materials and products. The obtained results prove that vehicle type 1 is the most used, followed by type 2, and type 3 is not used in the network; according to the objectives of the problem, energy consumption and cost of types 1 and 2 are reasonable.

Table XI. Number and type of vehicles used along the CLSC

Facilities	Vehicle type 1	Vehicle type 2	Vehicle type 3
Suppliers	102	7	---
Production centers	49	4	---
Distribution centers	40	10	---
Customers	9	3	---
Collection centers	11	1	---
Disassembly centers	16	---	---
Renovation centers	4	---	---
Recycling centers	54	12	---

In the results obtained and presented in *Fig. 8,* it was investigated to find out if there is a fluctuation in the demand for finished products, as well as how and with what sensitivity level the supply chain will react to these changes. To achieve this purpose, at each stage, the current demand has been increased compared to the previous demand by 25%. This process continues until the demand becomes twice as big as the current demand. The sensitivity analysis in the number of production and collection facilities has been investigated. In the first stage, or the current demand, the number of facilities required for production is four centers and one for collection centers. In the next stage, the production centers will be increased to five, but the number of collection centers will remain unchanged. When demand doubles, eight production centers and two collection centers are needed. According to these observations, it is concluded that production centers are more sensitive to demand changes and collection centers show less sensitivity. This makes sense considering these issues: the number of collection centers depends on the number of returned products, and the number of these products is less than the demand of the final product. Also, the capacity of the collection centers is more than the production facilities.

Fig. 9 examines the response of the costs of different network levels to changes in the percentage of returned products in proportion to the demand for the final products. In each step, 10% is added to the percentage of returned products compared to the demand, until 50% of the final products enter the reverse flow of the supply chain after their life-end. As expected, with the increase in returned products due to the return of refurbished parts and raw materials to the production cycle, supply costs will decrease. Due to the need for more processing (results for processing cost in *Fig. 9* must be multiplied by 10) and increasing the frequency of transportation between facilities, the costs in these two sectors increase. Regarding the costs of establishing facilities in the network, by increasing the returned products to 20%, there is a need for fewer facilities in the direct flow. Due to the higher capacity of the centers in the reverse flow, their numbers remain constant, so the costs of setting up facilities in the network are reduced. With the continuous increase in the percentage of returned products, there is a need to establish more facilities in the return flow of the supply chain. As a result, the costs of building the facilities will increase and then a balance will be established in the network.

In addition to the economic sector, changes in the percentage of returned products compared to the demand also affect the energy consumption at different levels of the network. *Fig. 10* examines and analyzes the sensitivity of these levels concerning the changes in the percentage of returned products. For the supply sector in the supply chain, the energy consumption of suppliers will decrease and costs for the need to purchase raw materials and parts are reduced. The analysis of the sensitivity of energy consumption of other levels of the network to these changes is consistent with the reaction and sensitivity of the economic issue of the network that was mentioned.

Fig. 11 presents the analysis of the results on the transportation system in different scenarios. Using vehicle type 1, as the most used vehicle in the transportation strategy of the model to transport materials and products in the network due to its low capacity, will increase the number of trips, which ultimately increases fuel consumption and costs. Using the other two types also has worse results. This sensitivity analysis shows the superiority of heterogeneous versus homogeneous vehicle fleets for reducing costs and energy consumption according to the designed supply chain.

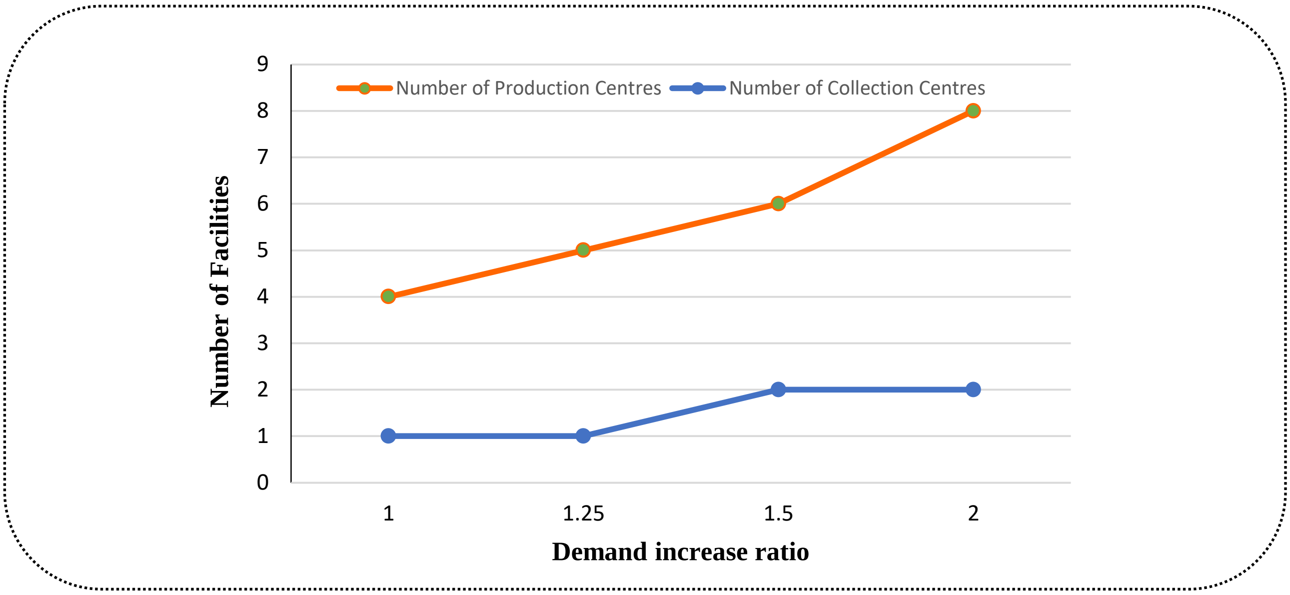


Fig. 8. The sensitivity of production and collection centers number to the demand increase

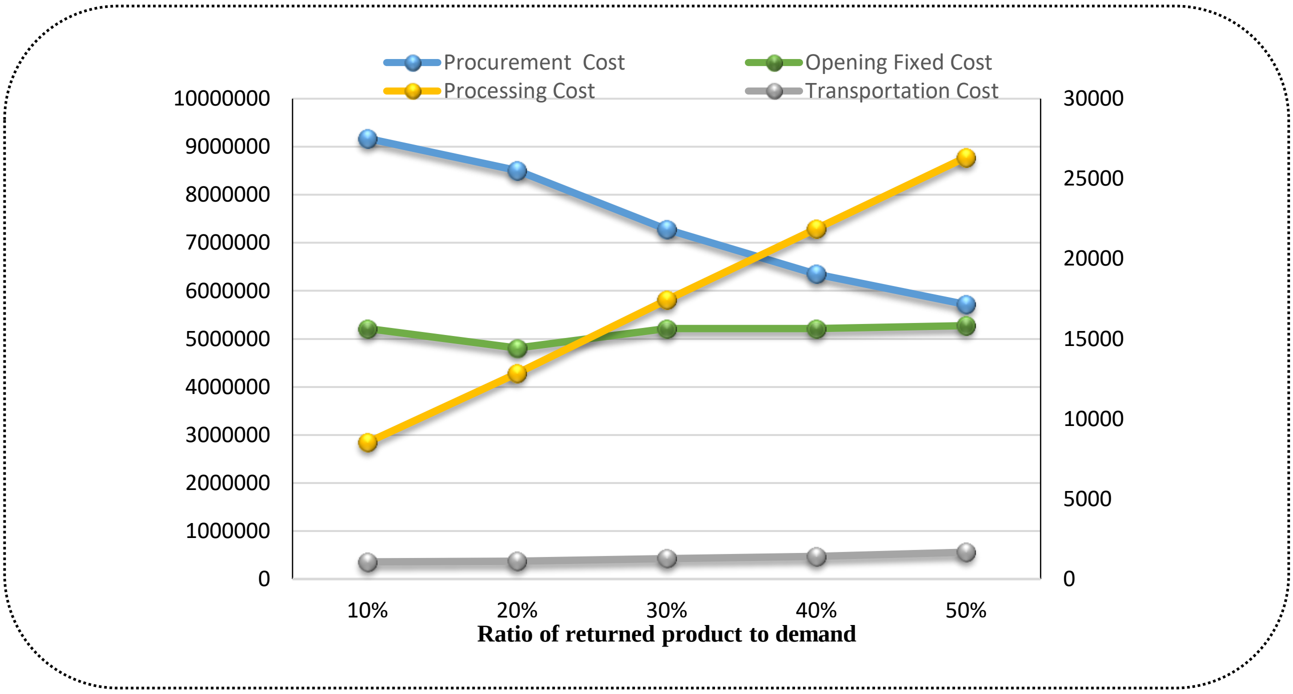


Fig. 9. Performances of cost concerning number of returned products

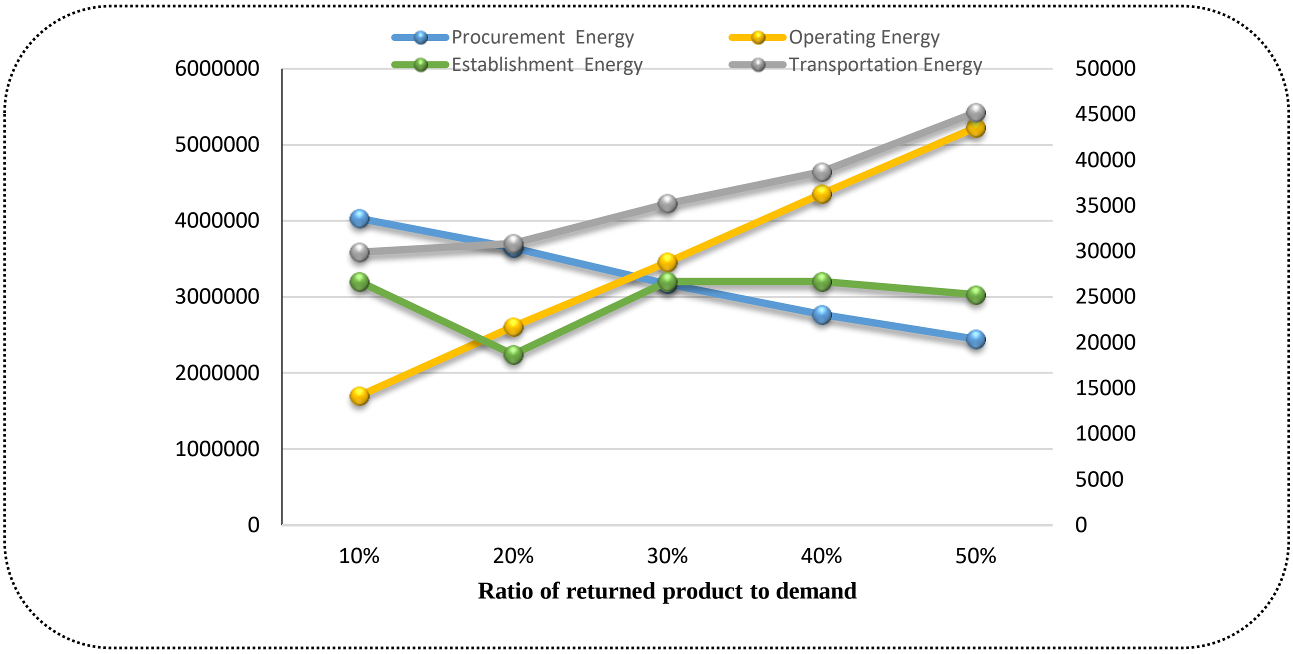


Fig. 10. Performances of energy consumption concerning the number of returned products

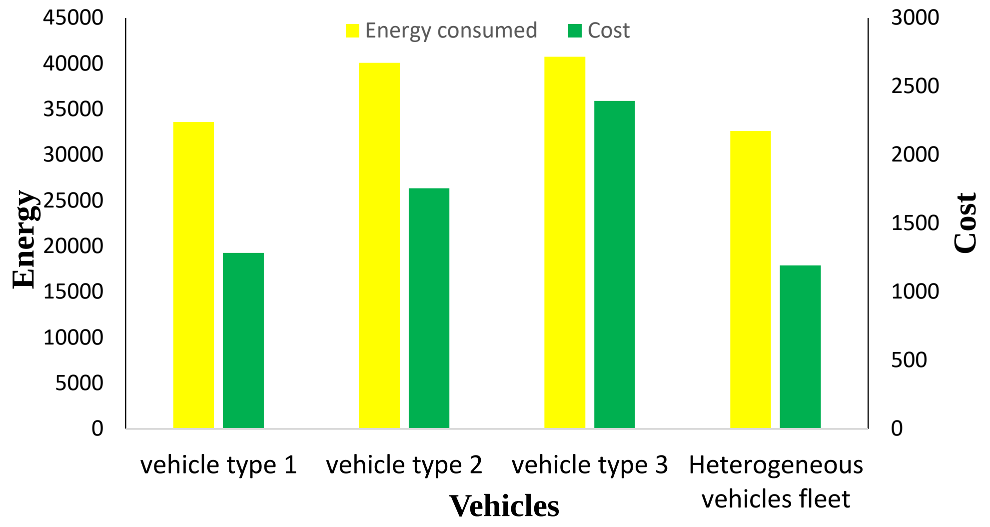


Fig. 11. Sensitivity analysis of vehicles fleet

B. Implementing medium and large-sized scenarios by MOPSO and NSGA-II

To evaluate the performance of the algorithms in solving medium and large-sized problems, five different scenarios are created. These scenarios are solved using both algorithms, and the results are compared. *Fig.* 12 illustrates the scenarios created for different sizes.

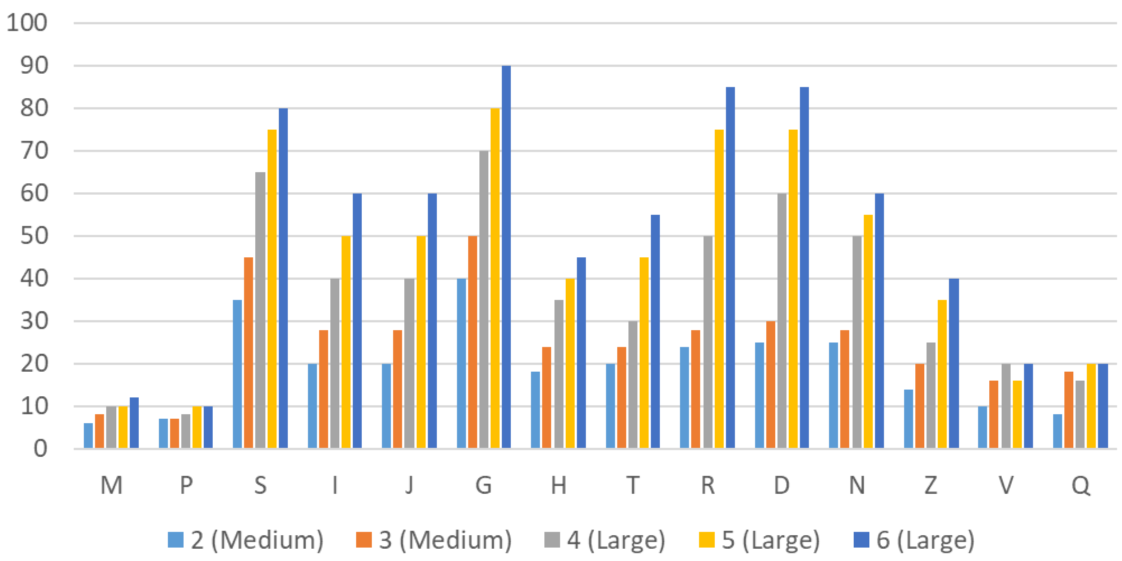


Fig. 12. Input parameters in medium and large size scenarios

Table XII. The best solution of each objective function in the set of Pareto solutions for each scenario from the two-solution methods NSGA-II and MOPSO.

Scenario	Method	Cost objective	Energy consuming	Social objective
2	NSGA-II	114305844.6635	62334530.9922	6061.9185
	MOPSO	147960963.0826	72099981.0513	6860.0312
3	NSGA-II	158390475.7012	88756490.2374	10124.7896
	MOPSO	220588367.8072	110248589.8618	12374.8029
4	NSGA-II	278232992.2043	186949423.6501	15668.4224
	MOPSO	333301629.399	203638433.1222	13179.3698
5	NSGA-II	387040845.4765	251189753.7601	22038.8512
	MOPSO	455876543.063	330137892.9532	22173.4399
6	NSGA-II	408919571.4001	336488864.8409	26044.5014
	MOPSO	636474775.7759	370764768.2714	25382.8771

As shown in Table XII, the performance gap between the two methods widens in larger scenarios (Scenarios 4 to 6) in the current model, where NSGA-II maintains a significant advantage in cost and energy objectives, while MOPSO retains its competitive strength in the social objective. This divergence could be attributed to NSGA-II's ability to better manage the increased complexity and multi-dimensionality of larger problems, which typically involve more variables and constraints.

C. Analysis of small, medium, and large size numerical examples

In the realm of supply chain management, the choice of optimization algorithms can significantly impact the efficiency and effectiveness of operations. When examining the performance of NSGA-II and MOPSO across different scales of supply chain scenarios, several patterns emerge. *Fig.* 13 delves into the comparative analysis of these two prominent optimization algorithms across various supply chain scenarios. The performance metrics evaluated include MID (Mean Ideal Distance), SNS (Spread of Non-dominance Solutions), DM (Diversity Metric), and NPS (Number of Pareto Solutions).

Fig. 13. Comparison of MID, SNS, DM and NPS for MOPSO and NSGA-II through scenarios

According to *Fig.* 13, the analysis begins with the MID, where NSGA-II generally shows more consistent performance compared to MOPSO, particularly in larger scenarios. This consistency might be attributed to NSGA-II's sorting mechanism, which efficiently manages multiple objectives, maintaining a balance between exploration and exploitation of the solution space. For the SNS metric, which evaluates the spread of solutions, both algorithms demonstrate fluctuations across scenarios, but NSGA-II exhibits less variability. This suggests a lower sensitivity to changes in the size or conditions of the supply chain model, implying a robustness that is crucial for managing less complicated models efficiently. In contrast, MOPSO shows a higher variance, possibly due to its stochastic nature and the influence of swarm dynamics, which might not consistently handle the spread of solutions as effectively as NSGA-II.

In terms of the Diversity Metric (DM), NSGA-II indicates a steady rise in performance with scaling scenarios, with a notable dip in the fourth scenario. On the other hand, MOPSO displays marked instability, particularly between the second and third scenarios, suggesting potential issues in adapting its parameters or mechanisms to scale efficiently. When analyzing the NPS, NSGA-II consistently outperforms MOPSO, indicating a superior capacity to generate diverse optimal solutions. This performance is pivotal for complex supply chain models where multiple optimal solutions are often necessary to cater to different objectives or operational constraints. While MOPSO maintains a lower and more consistent count of solutions, it shows a narrower approach, which may limit its effectiveness in scenarios requiring a wide range of strategic options. NSGA-II's overall consistency and robustness make it a suitable choice for scenarios that demand reliability and adaptability across different scales. However, MOPSO sometimes outperforms NSGA-II in specific metrics like DM, suggesting it may be more effective in environments where exploring diverse solution spaces is crucial, especially in more extensive and complex setups. The variation in performance between the two algorithms underscores the importance of selecting an appropriate metaheuristic based on the specific characteristics of the supply chain problem. Collectively, NSGA-II appears to perform more consistently and adapt better to varying conditions, maintaining a superior capacity to find multiple optimal solutions. However, MOPSO struggles with consistency and stability across different scenarios despite performing well in certain conditions.

D. Discussion

In this section, the results are compared with several previous relevant studies. Furthermore, it is mentioned how the obtained results can help managers make decisions. Fathollahi-Fard et al. (2018) designed a multi-objective model to reduce the cost and raise the social status of the CLSC network. Their results show the importance of job opportunities created by the supply chain along with the significance of the economic aspect. However, the environmental aspects are given little attention. They addressed the issue of respecting employee rights in various facilities, which in our model is considered and discussed as a training issue. In the return flow model developed by Fathollahi-Fard et al. (2018), products either are returned to the production cycle or are disposed of after the end of their life, which is one of the differences between these two studies. In the current study, raw materials that do not have the required quality to be reused in production are classified into two groups. One group is sent to disposal centers, and the other group is sent to the market for the recycled materials to preserve resources based on their quality to be used in other production networks. Another noteworthy difference is that in that model, the flow rate of material and products at different levels of the network is specified, but vehicles and methods of transportation strategy are not mentioned.

Keshavarz-Ghorbani and Pasandideh (2023) considered the cost and the social aspect in the model they have developed for the design of the CLSC. However, the environmental factors are overlooked in their model. Examining the results demonstrates a great focus on economic issues to reduce costs and increase profits. In the discussion part of their study, they discussed the importance and impact of returned products to the production cycle on the overall costs of the network, especially the costs of supplying raw materials. This is in alignment with the results obtained in the current study. The increasing number of job opportunities in the network due to the reverse supply chain demonstrates its importance in improving the social status of the network. In their developed model, the products that have the required quality for reproduction are collected, and no scenario has been determined for the products that do not have the required quality after the end of their lives. In the current model, to solve this problem, the products are collected, their quality is controlled in the relevant centers, and their fate is decided upon by the appropriate managers. Some are returned to the production cycle, some are sold in the recycling market, and the rest are sent to safe disposal centers to protect the environment.

For the design of a sustainable supply chain, a model has been presented by Rahbari et al. (2023a), which focuses on preventing the financial bankruptcy of the network. Their results show that considering economic issues alone may not be enough to prevent bankruptcy from happening, and both the environmental and social aspects must be considered. Their results, which are in alignment with ours, demonstrate the superiority of using a heterogeneous vehicles fleet compared to a homogeneous vehicles fleet. One of the differences between these two articles is that in Rahbari's model, the reduction of carbon dioxide emissions is considered a financial penalty in the cost objective function to respect the environment. However, the model presented in this paper considers energy consumption as an important objective function. It is noteworthy that Rahbari's model fails to consider the supply chain in the form of a closed-loop which is important for the issue of sustainability.

Atabaki et al. (2020) designed a model for the CLSC of durable products, whose goals are to reduce costs, pollution, and energy consumption, and preserve resources. Considering job opportunities and employees' training to respect social responsibilities are the main differences between their studies and ours. Nevertheless, the results of these two studies are in alignment with each other and provide a common analysis. The interpretation of the results shows the portion of returned products as a significant parameter which affects economic issues and energy consumption. This leads to the conservation of resources. Both studies suggest increasing the quality of raw materials as well as finished products. They also suggest increasing the capacity of the reverse supply chain. The results show that this increase in capacity will initially increase the cost of setting up the facilities, but in the long term, it will reduce the network costs and increase its profits.

We examined the analysis of the obtained results with the relevant articles, and we found consistent results. We also discussed the differences between these studies, which arose from differences in data, assumptions, limitations, and the defined objectives of these articles. The results obtained from the solution of the developed model and its interpretation create practical and managerial insights for decision-makers in the supply chain. Furthermore, we will examine the most important of these managerial implications:

- One of the most important goals of any supply chain management is to find the optimal point and minimize the internal costs of the network. To achieve this goal, this integrated design of the model appears to be essential for the supply chain network. The results from solving this model, including the costs of different levels, the costs of setting up the required facilities, and finding the appropriate location to minimize the costs concerning other aspects of sustainability, help managers make strategic decisions.
- The analysis of the results of this model shows that the cost of purchasing raw materials covers a large portion of the cost of the supply chain. Therefore, the return of raw materials to the production cycle through returned products is effective in reducing costs.
- The results show that the number of returned products to the production cycle affects the network as a whole, in a way that increasing these returned products improves the performance of the network, especially in terms of costs and conservation of resources. The importance of choosing the most suitable suppliers, the quality of raw materials, and the reverse flow capacity of the network help to increase the portion of materials returning to the production cycle. The need to design the network in a closed-loop manner is supported by these results. However, it must be noted that, on one hand, establishing the facilities and the required technologies in the reverse flow would have a high cost. On the other hand, its economic profitability will take a long time to be in effect. As a result, investing for small and medium enterprises in the reverse flow of the network is very challenging and the need for governments to get involved and help them is evident.
- Meeting the demands and preferences of customers in full is one of the most important management goals to prevent sales losses. In this model, in addition to locating and proposing the establishment of production centers, their respective required amount of exploitation and the number of produced products in each unit have been determined

to cover the customers' demands and avoid additional production costs. This can ultimately lead to increasing customer satisfaction with the network.

- In addition to the economic aspect, in the current competitive market, it is imperative to consider the conservation of resources and energy for the supply chain's success. To reduce costs and energy consumption, the management's primary strategy for within-network transportation is to use the full capacity of the available vehicles. The heterogeneous vehicles fleet proposed by the authors of this article allows managers to use this strategy with various characteristics of its vehicles. The analysis of the results obtained from the proposed transportation fleet shows the optimal number of transports and the type of transport used. The comparison of the results between the use of a heterogeneous transport fleet and a homogeneous transport fleet clearly shows the superiority of the proposed fleet in both cost and energy consumption aspects.
- The governments' regulations regarding social issues as well as increasing the social status of the network among consumers in recent years, have caused the managers to be concerned about dealing with social responsibilities. This can be achieved by increasing job opportunities created through the supply chain. The developed model of this article, regarding network costs, considers the maximization of job opportunities to improve the social power of the supply chain. In addition, the topic of employee training is included in this model as a separate factor from the social dimension of sustainability. This increases the social status of the network among employees and ultimately leads to the improvement of their performances.

VI. CONCLUSION

This study proposed an integrated MILP model for CLSC design concerning sustainability. The first objective function is minimizing network cost, while the second and third functions cover the environmental aspects and social factors, respectively. These include job opportunities and workers' training. Accordingly, all levels of CLSC are taken into consideration, which helps decision-making at both strategic and operational levels. Supplier selection, facility location-allocation, selected production technology, transportation scenario, optimal costs, and energy consumption are outputs of this model. The NSGA-II and MOPSO methods have been employed to solve the problem and obtain the results in MATLAB software.

The results show that to consume less energy, the costs of the system would increase inevitably. Higher number of launched facilities results in the creation of more jobs by the network. This increase, which is in line with the social factors, causes more construction costs and staff training, and, consequently, more costs for the whole system. The reviewed results show the importance of returning products and their significant impact on preserving resources. These resources include raw materials and energy consumption, which notably reduces the system costs for all stages of production until the product reaches the customer. In conclusion, the results show the significance of the designed CLSC due to its commitment to returnable products and the implementation of all three pillars of sustainability.

Future studies can expand on the social dimension of sustainability by incorporating additional factors such as employees' well-being, community engagement, and fair labor practices, which are not comprehensively addressed in this study. Investigating the impact of supply chain operations on local communities and worker satisfaction can provide a more holistic understanding of the social implications of sustainable supply chains. Moreover, while this study focused on energy consumption, future research should also address environmental pollution issues, specifically carbon emissions. Including decarbonization strategies in the supply chain model would enhance its environmental sustainability. Researchers could explore the integration of renewable energy sources, carbon capture technologies, and other green initiatives to reduce the carbon footprint of supply chain operations. Additionally, future studies should consider network uncertainties such as demand fluctuations, supply disruptions, and transportation delays, and they should employ robust optimization methods to address these challenges. Stochastic modeling, scenario analysis, and resilient supply chain strategies can be utilized to develop more adaptable and reliable supply chain models.

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