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A multi-objective multi-echelon closed-loop supply chain with disruption in the centers

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Abstract *– Supply chain management has significant economic and environmental effects, including strategic, tactical, and operational decisions. According to the need for further cost reduction and improving the process of the organization in the direction of customer demand, the concept of the supply chain has become increasingly important, and the organizations seek to expand this concept within their organizational framework. In this regard, efficient planning of products distribution in the supply chain considering disruption is very important. Thus, this study develops a multi-objective mixed-integer programming mathematical model to design a green multi-echelon closed-loop supply chain with the possibility of disruptions. Furthermore, the ε-constraint method is applied to solve and validate the proposed model in small-scale problems. On the other hand, a non-dominated sorting genetic algorithm is developed for solving large-sized problems. Results indicate that the proposed model has performed well in obtaining optimal solutions, and the proposed algorithm has an efficient performance.*

Keywords– *closed-loop supply chain, green supply chain, customer satisfaction, ε-constraint method, NSGA-II.*

I. INTRODUCTION

Supply Chain Management refers to the effective management of the materials, information, and capital flows all over various supply chains, including suppliers, manufacturers, distributors, retailers, and customers (Chopra and Meindl, 2016). An efficient supply chain is critical to optimize resources, increase profitability and customer satisfaction. The environmental concerns and awareness of social responsibility have led the whole community, researchers, and managers to design sustainable supply chains (SSCs) combining economic, environmental, and social factors (Zhang et al.,2019).

A forward supply chain (FSC) is a network with different layers such as suppliers, manufacturers, warehouses, and distribution centers where raw materials are converted to final products and distributed to customers (Santoso et al., 2005). The closed-loop refers to the integration of forward and reverse supply where forward flows manage customers'

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demand and reverse ones are responsible for collecting and recovering returned products (Banasik et al., 2017; Haddadsisakht and Ryan, 2018).

The issue of the closed-loop supply chain has attracted much attention because it ensures the sustainability of many different industries (Salehi-Amiri et al., 2021). Closed-loop supply chain network design has received increasing attention in the last decade, where it focuses on economic, resource utilization, and sustainability maximization through incorporating both forward and reverse logistics (Yu and Solvang, 2020). due to the competitive market environment, the importance of the problem of designing a closed-loop supply chain network as one of the key issues to achieve a competitive advantage has become more and more the attention of managers and researchers. On the other hand, this problem is always accompanied by uncertainty, which may lead to some issues in the decision problem. Today, the importance of sustainable development has convinced supply chain managers to move their network toward sustainable supply (Nayeri et al.,2020).

Designing a logistic network is inherently a strategic decision, which usually involves locating the facilities, their capacity, and the number of products, the number of categories in the chain, and how the facility communicates. All of these issues have a significant impact on efficiency and, consequently, the performance of the supply chain. As it takes a lot of time and money to build or close the facilities, it is not possible to change them in the short term. A new concept that has been expressed in the field of chain communication recently is communication disruption among the levels. For example, when transferring raw materials from the supplier to the manufacturer, a disruption occurs, and it is impossible to supply specific raw materials from one supplier to another. In this study, a closed-loop supply chain including suppliers, producers, distributors, and customers in the forward flow and the collection, recovery, and disposal center in the reverse flow is considered, such that there is a possibility of disruption in distribution centers while distributing the products. According to the literature of the issue, the strategies for facing the disruption of distribution centers and how to serve the customers are as follows (Azad et al., 2013):

- There is no disruption in the distribution center, and the center can fully serve the allocated customers.
- Disruption in the distribution center has occurred entirely, and customer service should be done using other distribution centers.
- There is a minor disruption in the distribution center, but there is still the ability to serve the customers. In this case, part of the needs of customers is met by this distribution center, and the other part is provided through other distribution centers.

In the literature, the first and second strategies have been studied most, while the first and third strategies are to be used in this study.

On the other hand, in recent years, economic and technological advances have improved living standards and posed significant environmental and social challenges such as reducing resources, water pollution, and waste. Thus, there has been a great focus on environmental friendliness and sustainable development by global governments, corporations, and society as a whole (Darbari et al., 2019; Yu and Solvang, 2016, Yu and Solvang, 2020).

In this study, a mathematical model is developed to design a green closed-loop supply chain considering disruption in distribution centers. To validate the proposed model, a multi-objective MIP model is first transformed into a single-objective model by the ε-constraint approach and then is solved by generating numerical samples using a CPLEX solver. Furthermore, an NSGA-II algorithm is developed to solve the problem on a large scale.

In the following, Section 2 reviews the literature of the research in the form of previous studies. The proposed problem and the proposed modeling are presented in Section 3. Section 4 includes solution approaches for the problem. The validation of the proposed model and the computational results of the research are presented in Section 5, and finally, in Section 6, the conclusions and future suggestions are described.

II. LITERATURE REVIEW

In this section, the literature of the forward, reverse, and closed-loop supply chains are studied, and then, studies related to the supply chain disruption are reviewed.

Niknejad and Petrovic (2014) presented an integrated reverse logistics network with different recycling routes. For this purpose, a fuzzy mixed integer programming model was developed. Ramezani et al. (2014) presented a financial approach to design a closed-loop supply chain network. Financial aspects such as fixed and current assets and liabilities were considered exogenous variables in the network. Also, to analyze the sensitivity of the parameters, the analysis of variance method has been used. Soleimani and Kannan (2015) designed a large-scale multi-period, multi-level, multi-product closed-loop supply chain network. The purpose of this study was to minimize the fixed costs of raw materials, production, purchase, shortage, recycling, reproduction, transportation, inventory maintenance, repair, and destruction. They combined genetics and particle swarm optimization algorithms in order to improve the efficiency of the genetic algorithm.

Dondo and Méndez (2016) developed an operational planning model for forward and reverse logistics activities in a multi-level network and investigated the issues of distribution and recovery in their problem. In order to solve the proposed problem, an analysis-based approach was developed to achieve near-optimal solutions. Mohammed et al. (2017) investigated a green closed-loop supply chain with multi periods considering uncertainty. In this study, a scenario-based approach was used to deal with uncertainty. For this purpose, a MILP model was developed. Mohammed et al. (2018) studied a closed-loop supply chain network design considering carbon policy under uncertainty. They developed a robust optimization model to solve the model. They applied three policies, including carbon cap, carbon tax, and carbon cap and trade.

Hasanov et al. (2019) developed a tradeoff model between cost and greenhouse gas emission for a four echelon CLSC that considered remanufacturing in reverse logistics. Zarbakhshnia et al. (2019) proposed a multi-objective model for sustainable CLSCND to minimize cost, carbon emission, and the number of machines simultaneously using the e-constraint method. Zhang et al. (2019) presented a multi-objective robust fuzzy closed-loop supply chain network (CLSCN) design model under uncertainty to minimize total cost, carbon caps, and social impacts maximization.

Yu and Solvang (2020) proposed a fuzzy multi-objective model for a sustainable closed-loop supply chain under uncertainty to balance the cost and environmental aspects of various kinds of uncertainty. Firstly, the model is defuzzified, and then an average sample approximation-based weighting method is applied to obtain a set of optimal solutions. Guo et al. (2020) studied a closed-loop green supply chain considering government subsidies in the business environment. Used traditional optimization methods, meta-heuristic methods, genetic algorithms, and particle swarm optimization to find and calculate the approximate optimal solution. The results of the calculation showed that companies could properly adjust the production and restructuring ratio to achieve the desired result of the system.

Alegoz et al. (2020) examined the economic and environmental effects of closed-loop supply chains based on total cost and carbon emissions. They developed two-step stochastic models for the forward and closed-loop supply chains design. They found that the loop closing may be beneficial to companies. Salehi-Amiri et al. (2021) designed a sustainable closed-loop supply chain network for the walnut industry. They proposed a new MILP model to minimize total costs. The designed network not only considered forward and reverse flow to meet the needs of different markets, but also the preparation of return products for second use.

Moreover, various studies have been conducted on the issue of disruption in the supply chain. Azad et al. (2013) studied a supply chain network problem by considering the disruption in the two sectors of transportation and equipment and proposed a benders decomposition approach in order to solve it. This study aimed to determine the optimal location and type of distribution centers as well as allocating the customers to distribution centers. In this study, the strategies which were considered for the disrupted distribution centers had a new concept compared to similar studies. In other words, there is a partial disruption in the distribution center and is still able to provide services, but not completely. So, part of the service is done by the disrupted center, and the rest is done by another distribution center. In this regard, a MIP model was developed. Furthermore, an analysis of various components of the problem was performed to identify the factors affecting system performance.

Teimuory et al. (2013) proposed a multi-objective programming model for the supply chain problem with disruption. In this study, a three-level supply chain including customers, distribution centers, and suppliers was considered, and the goal was to minimize the costs and maximize reliability. The costs considered in this study include the fixed costs of reopening the centers, the cost of inventory, the cost of transportation, and the cost of penalties due to the shortages. In addition, the variance of inventory maintenance, transportation, and shortage costs was considered minimized. Hatefi and Jolai (2014) provided a robust model for forward and reverse logistics network design with the possibility of equipment disruption and demand uncertainty. Accordingly, a MIP model with added robust constraints was developed to control network reliability in scenarios to minimize the costs and reduce the risk of disruptions. In order to study the robust behavior and reliability of the logistics network, several numerical examples were considered. Also, in order to evaluate the performance of the proposed robust criterion compared to other robust criteria in the literature, a comparative analysis was performed.

In another study, Hatefi et al. (2015) solved the same problem employing the mathematical programming method of credibility constraint. In this study, in order to evaluate the performance of the proposed model, several numerical examples were generated, and sensitivity analysis was performed. Torabi et al. (2015) proposed a stochastic programming approach for designing a reliable closed-loop supply chain network, taking into account the possibility of partial and general disruption in equipment and uncertainty of some parameters. To do this end, a stochastic MILP model was developed, which aimed to minimize the reopening cost of equipment and the expected cost of disruption. Computational results showed that operational risks and disruptions affected the network structure significantly.

Hasani and Khosrojerdi (2016) studied a robust supply chain considering uncertainty and disruption. Accordingly, MIP models, as well as an efficient Taguchi-based memetic algorithm, were developed. In this study, the Lagrangian Relaxation approach was employed to evaluate the solution quality and efficiency of the proposed memetic algorithm. Ivanov et al. (2017) investigated a supply chain with an emphasis on environmental components such as pollution and waste in disruptive conditions. The proposed supply chain was multi-period, multi-level, and multi-product. In this problem, the objectives were minimization of return flow, maximization of throughput, and minimization of inventory. Computational results proved that considering the recovery capacity leads to the minimization of disruptions relevant to the reverse flow. Jabbarzadeh et al. (2018) studied a closed-loop supply chain with disruption which aimed to minimize total cost. They developed a robust stochastic optimization model that determines the optimal location of equipment and the amount of displacement between different levels of the chain. A Lagrangian relaxation algorithm was developed to solve the robust model. Furthermore, to evaluate the performance of the proposed optimization model, real data from the glass production and distribution industry were used. The computational results represented a better performance of the proposed model in cost savings.

Diabat et al. (2019) proposed a robust bi-objective optimization model for the supply chain design of perishable goods considering disruption and reliability. The purpose of this study is to minimize the time and cost of sending products to customers after a crisis while there is a possibility of equipment disruption and the route between them. In order to solve the proposed bi-objective problem, a Lagrangian-based and Epsilon constraint release-based solution approach has been developed. In order to validate the proposed model, a real case study has also been evaluated. Yavari and Zaker (2020) investigated the supply chain problem of green closed loops resistant to perishable products in disturbance conditions in power grids and supply chains. In this regard, to deal with the disruption of the electricity network, a supply chain has been integrated with the electricity network. Resistance strategy has also been used to deal with supply chain disruptions. For this purpose, a bi-objective linear programming model has been developed. In addition, a case study related to the Iranian Dairy Company has been considered. Hamdan and Diabat (2020) designed a robust blood supply chain network at risk of disruption. For this purpose, a robust two-stage robust optimization model has been developed. The aim of this study was to minimize the time and cost of sending blood to the hospital after a crisis. Accidental disruption is also considered in collection centers, blood banks, and transportation routes. In order to solve the model, the Lagrangian release approach has been used. Table I summarizes the most important and relevant research conducted in recent years.

According to the literature, this study is intended to present a mixed-integer linear mathematical planning model to design a green closed-loop supply chain by considering the disruption in the distribution centers. Finally, after reviewing the literature, it is concluded that the research gap includes the following:

1. In this study, a green closed-loop supply chain network is developed, in which there are four levels of the supplier, producer, distributor, and customers in the forward flow, and the reverse flow contains a collection, disposal, and recovery center. In the literature review, a small number of papers studied a multi-objective problem. In this paper, three objectives, such as cost and environmental pollution minimization and maximization of customer satisfaction, are considered.
2. One of the distinguishing features of this research is the type of disruption in the network. While equipment, distribution center, or other centers are disrupted separately or in pairs in other studies, supply and collection centers will also be disrupted in this study, in addition to equipment and distribution centers.
3. Customer satisfaction level as an objective function has been applied for the first time in the disruption case.
4. We are developing the ε-constraint method and NSGA-II algorithm to validate and treat the problem.

III. PROBLEM DESCRIPTION

The closed-loop supply chain usually consists of several levels in the forward and reverse flow. A new concept of this field is the disruption of communication between the levels. For example, when raw materials are transferred from the supplier level to the producer, disruption can occur, and as a result, a customer cannot be supplied with a specific product.

In this study, a closed-loop supply chain including four levels of the supplier, producer, distributor, and customer in the forward flow and three levels of collection, recovery, and disposal in the reverse flow is considered. Moreover, there is a possibility of disruption in distribution centers while distributing products to customers. Figure 1 shows the proposed closed-loop supply chain network.

Table I.Summary and comparison of closed-loop supply chain research with current research

Disruption type			***Solution method***			***Modeling approach***				***Objective***		***Supply chain***					
Other center	***Distribution center***	***Equipment***	***Metaheuristics***	***Heuristics***	***Exact***	***Robust***	***Fuzzy***	***Stochastic***	***Deterministic***	***Multiple***	***Single***	***Closed-loop***	***Forward and reverse***	***Reverse***	***Forward***	***Year***	***Author(s)***
✓		✓		✓					✓		✓				✓	2013	Azad et al.
✓	✓		✓						✓	✓					✓	2013	Atoei et al.
✓	✓				✓			✓		✓					✓	2013	Teimuory et al.
		✓			✓	✓					✓		✓			2014	Hatefi & Jolai
		✓			✓			✓			✓		✓			2015	Hatefi et al.
		✓			✓	✓					✓		✓			2015	Hatefi & Jolai

Continue Table I.Summary and comparison of closed-loop supply chain research with current research

Disruption type			*Solution method*			*Modeling approach*				*Objective*		*Supply chain*				*Year*	*Author(s)*
Other center	*Distribution center*	*Equipment*	*Metaheuristics*	*Heuristics*	*Exact*	*Robust*	*Fuzzy*	*Stochastic*	*Deterministic*	*Multiple*	*Single*	*Closed-loop*	*Forward and reverse*	*Reverse*	*Forward*		
		✓			✓			✓		✓		✓				2015	Torabi et al.
✓			✓	✓					✓		✓				✓	2016	Hasani & Khosrojerdi
✓					✓				✓	✓					✓	2017	Ivanov et al.
✓				✓		✓					✓	✓				2018	Jabbarzadeh et al.
		✓			✓	✓					✓				✓	2019	Diabat et al.
	✓				✓			✓		✓		✓				2020	Hamdan & Diabat
✓					✓	✓				✓					✓	2020	Yavari & Zaker
✓	✓				✓				✓	✓		✓					Current Work

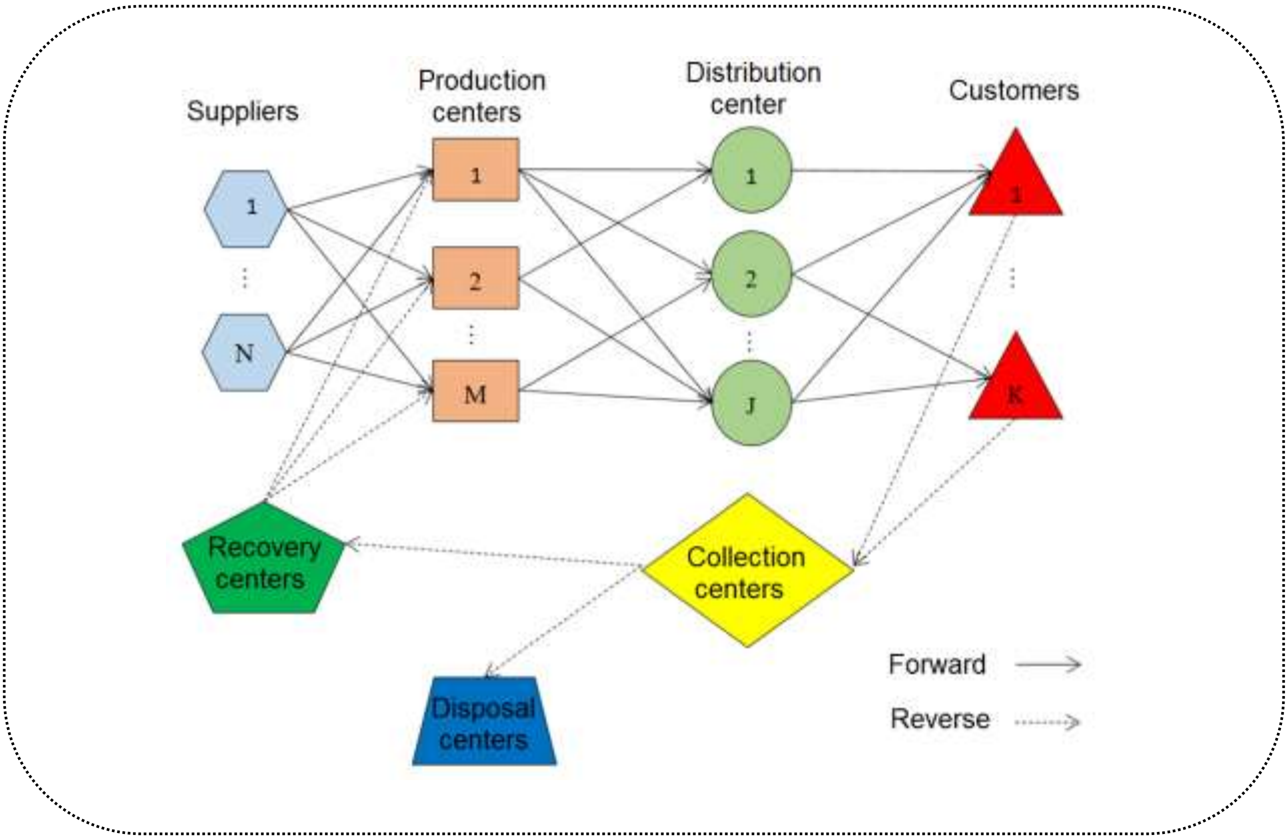

Figure 1. The proposed supply chain network

This study aims to determine the quantity of the product delivered by distribution centers to customers so that the total cost of the supply chain network and the emission of pollutants are minimized. In this study, the possibility of disruption in distribution centers is considered, which means that there may be disruptions in serving the customers, and it will not be possible to fully meet the customer demand from that distribution center. The costs of the proposed network include the costs of reopening the centers, transportation costs, the cost of disruption, and the cost of environmental pollution. In the following, the assumptions of the proposed closed-loop supply chain network are presented.

- The supply chain is closed-loop
- The forward flow of the proposed supply chain includes supply, production, distribution, and customer centers
- The reverse flow of the supply chain includes the collection, disposal, and recovery centers.
- The distribution network includes two types of reliable and unreliable distribution centers.
- Two types of safe and unsafe transportation are assumed.
- Only one type of product is considered.
- The demand of customers is known at the beginning of the planning horizon.
- There is a fixed cost for reopening the supply centers, production centers, and distribution centers.
- The maximum capacity for distribution centers is specified.

Sets, indices, parameters ,and variables of the problem are as follows:

Sets and indices

s : supply centers $s \in S$

c : collection centers $c \in C$

m: production centers $m \in M$

o: recovery centers $o \in O$

j: distribution centers $j \in J$

d : disposal centers $d \in D$

k : customers $k \in K$

r: unsafe transport mode between the distribution center and customers $r \in R$

Parameters

sm_m : set up cost of production center m

GHu_{jk} : Volume of emission for transferring a unit from unreliable distributor j to customer k

pc_m : Unit production cost in production center m

dr_{jk} : Transportation cost between reliable distributor j and customer k

p_m : Unit selling price in production center m

GHr_{jk} : Volume of emission for transferring a unit from reliable distribution center j to customer k

pf : Failure Cost of product

uc_{ij} : Transportation cost from reliable distribution center i to unreliable distribution center j

D_k : Customer k demand

GH_{ij} : Volume of emission for transferring a unit from reliable distribution center i to unreliable distribution center j

fc_s : fixed cost of supplier s

tck_{kc} : Transportation cost from customer k to collection center c

fU_j : Fixed cost of reopening an unreliable distribution center j

GHk_{kc} : Volume of emission for transferring a unit from customer k to the collection center c

fR_j : Fixed cost of reopening a reliable distribution center j

tcc_{co} : Transportation cost from collection center c to recovery center o

sc_c : Collection center c setup cost

GHc_{co} : Volume of emission for transferring a unit from collection center c to recovery center o

so_o : Recovery center o setup cost

tcd_{cd} : Transportation cost from the collection center c to disposal center d

sd_d : Disposal center d setup cost

GHd_{cd} : Volume of emission for transferring a unit from collection center c to disposal center d

ope_o : Recovery cost in recovery center o per unit

tco_{om}: Transportation cost from recovery center o to production center m

opd_d : Disposal cost of center d per unit

GHo_{om}: Volume of emission for transferring a unit from recovery center o to production center m

stc_{sm}: Transportation cost from supplier s to production center m

A : The amount of required raw material to produce the products

GHs_{sm}: Volume of emission per transferring a unit from supply center s to production center m

cap_j : Capacity of distribution center j

tc_{mj}: Transportation cost from production center m to distributor j

$pcap_m$: Capacity of production center m

GHm_{mj}: Volume of emission for transferring a unit from production center m to distributor j

τ_j : A ratio of the total capacity of disrupted unreliable distribution center j

e_{jkr} : Transportation cost from unreliable distribution center j to customer k with unsafe transport mode r

q_j: The possibility of occurring disruption in the unreliable distribution center j

dp_{jk} : Transportation cost from unreliable distribution center j to customer k with safe transport mode r in the initial allocation

π_{jkr} : The possibility of occurring disruption between distribution center j and customer k while using unsafe transport mode r

db_{jk} : Transportation cost from unreliable distribution center j to customer k with safe transport mode r in the secondary allocation

ε_k: Product return coefficient for customer k

B: A very large number

Variables

Os_s : If the supply center s is reopened 1, otherwise 0.

Y_{kc} : If the returned product is sent from customer k to collection center c 1, otherwise 0.

Op_m : If production center m is reopened 1, otherwise 0.

Zo_{co} : If the product is sent from the collection center c to recovery center o 1, otherwise 0.

Oc_c : If the collection center c is reopened 1, otherwise 0.

Zd_{cd} : If the product is sent from the collection center c to disposal center d 1, otherwise 0.

Oe_o : If recovery center o is reopened 1, otherwise 0.

W_{om} : If the product is sent from recovery center o to production center m 1, otherwise 0.

Od_d : If disposal center d is reopened 1, otherwise 0.

a_{sm} : The amount of raw material supplied from supplier s for the production center m

XU_j : If unreliable distribution center j is reopened 1, otherwise 0.

X_{mj} : The amount of products transferred from production center m to distribution center j

XR_j : If reliable distribution center j is reopened 1, otherwise 0.

QY_{kc} : The amount of returned products from customer k to collection center c

YR_{jk} : If customer k is allocated to reliable distribution center j 1, otherwise 0.

QZo_{co} : The amount of products sent from collection center c to recovery center o

YS_{jk} : If customer k is allocated to unreliable distribution center j with safe transport mode 1, otherwise 0.

QZd_{cd} : The amount of products sent from the collection center c to disposal center d

Os_s : If the supply center s is reopened 1, otherwise 0.

QW_{om} : The amount of products sent from recovery center o to production center m

YM_{jkr} : If customer k is allocated to unreliable distribution center j with unsafe transport mode 1, otherwise 0.

T_{ij} : The amount of products transferred from reliable distribution center i to an unreliable distribution center j in case of disruption

A. Proposed mathematical model

In this study, a multi-objective model is developed for the green closed-loop supply chain problem, possibly disrupting distribution centers. The objective functions of the problem include minimizing the total costs of the supply chain and the total volume of environmental pollution. The first objective function expresses the total cost, which consists of ten parts: the costs of reopening centers, production cost, cost of transportation between centers, and the cost of system disruption. The third objective function is to maximize the level of customer satisfaction. In other words, customer dissatisfaction is minimized. In this study, customer dissatisfaction is a percentage of customer demand that is met by an unreliable distribution center with an unsafe mode of transportation. Each of these objective functions is described below.

$$\begin{aligned}
Min\ Z_1 = & \sum_s fc_s \times Os_s + \sum_m sm_m \times Op_m + \sum_m \sum_j pc_m \times X_{mj} \\
& + \sum_s \sum_m stc_{sm} \times a_{sm} + \sum_m \sum_j tc_{mj} \times X_{mj} + \sum_j fU_j \times XU_j \\
& + \sum_j fR_j \times XR_j + \sum_c sc_c \times Oc_c + \sum_o so_o \times Oe_o \\
& + \sum_d sd_d \times Od_d + \sum_j \sum_k dr_{jk} \times D_k \times YR_{jk} \\
& + \sum_j \sum_k \sum_r (1-\pi_{jkr}) \times e_{jkr} \times D_k \times YM_{jkr} \\
& + \sum_j \sum_k dp_{jk} \times D_k \times YS_{jk} + \sum_j \sum_k \sum_r \pi_{jkr} \times db_{jk} \times D_k \times YM_{jkr} \\
& + \sum_i \sum_j q_j \times uc_{ij} \times T_{ij} + \sum_k \sum_c tck_{kc} \times QY_{kc} \times Y_{kc} \\
& + \sum_c \sum_o tcc_{co} \times QZo_{co} \times Zo_{co} + \sum_c \sum_d tcd_{cd} \times QZd_{cd} \times Zd_{cd} \\
& + \sum_o \sum_m tco_{om} \times QW_{om} \times W_{om} + \sum_o \sum_c ope_o \times QZo_{co} + \sum_d \sum_c opd_d \times QZd_{cd} \\
& + \sum_m \sum_o pc_m \times QW_{om} \times W_{om} + \sum_k \sum_c pf \times QY_{kc} \times Y_{kc} - \sum_m \sum_j p_m \times X_{mj}
\end{aligned} \quad (1)$$

Eq. 1 represents the first objective function of the problem, which involves minimizing the total cost of the supply chain. This objective function was the contribution of Azad et al. (2013). Since their study investigated a three-level problem, only one objective function consisting of 7 terms was considered. But in this study, a closed-loop supply chain problem is considered, and its first objective function consists of 24 terms.

The first term calculates the supply cost of raw material, which is based on the fixed cost of using the supply centers. The second term calculates the setup cost of production centers. The total cost of production is calculated through the third term. The fourth term shows the cost of transportation-related to the supply of raw materials between supply and production centers. The fifth term expresses the cost of transportation between production centers and distribution centers. The sixth and seventh terms show the cost of reopening unreliable and reliable centers, respectively. The terms eight to ten indicate the setup cost of collection, recovery, and disposal centers, respectively. The eleventh statement calculates the cost of allocating customers to reliable distribution centers. The expected cost of allocating customers to unreliable distribution centers with the safe and unsafe mode of transportation is shown in Figures 12 and 13, respectively. The eleventh term calculates the cost of allocating customers to reliable distribution centers. The expected cost of allocating customers to unreliable distribution centers with a safe and unsafe mode of transportation is shown in the twelfth and thirteenth terms, respectively. The fourteenth term indicates the expected cost of allocating customers to unreliable distribution centers while disruption happens and unsafe transport mode is selected. Also, the cost of transportation between reliable and unreliable distribution centers is calculated using the fifteenth term. The sixteenth term shows the cost of transportation between customers and collection centers. The seventeenth and eighteenth calculate the cost of transportation between collection centers and recycling centers, respectively. The cost of transportation between recovery centers and production centers is also obtained from the nineteenth term. The twentieth term shows the total cost of recovering the returned products. The twenty-first term calculates the total cost of disposal of products. The twenty-second term represents the cost of reproducing the returned products, and the twenty-fourth term shows the failure cost of the produced products. Finally, the last term expresses the revenue from selling the products.

In addition to minimizing the costs of the supply chain, environmental factors are also considered in the problem. So, the second objective function aims to minimize the total emissions in the proposed closed-loop supply chain.

$$\begin{aligned} Min\ Z_2 = &\sum_s \sum_m GHs_{sm} \times a_{sm} + \sum_m \sum_j GHm_{mj} \times X_{mj} \\ &+ \sum_j \sum_k GHu_{jk} \times D_k \times (YS_{jk} + YM_{jkr}) \\ &+ \sum_j \sum_k GHr_{jk} \times D_k \times YR_{jk} + \sum_i \sum_j q_j \times GH_{ij} \times T_{ij} \\ &+ \sum_k \sum_c GHk_{kc} \times QY_{kc} \times Y_{kc} + \sum_c \sum_o GHc_{co} \times QZo_{co} \times Zo_{co} \\ &+ \sum_c \sum_d GHd_{cd} \times QZd_{cd} \times Zd_{cd} + \sum_o \sum_m GHo_{om} \times QW_{om} \times W_{om} \end{aligned} \quad (2)$$

Equation 2 shows the second objective function of the problem, which minimizes the total emissions. This objective function was the contribution of Jamshidi et al. (2012). In their study, only the pollution between four levels was considered. While in this study, an objective function is developed for the total emission of pollution caused by transportation in a seven-level closed-loop supply chain. The first term calculates the volume of emissions for transportation between suppliers and production centers. The second term shows the volume of emissions for transportation between production and distribution centers. The third and fourth terms calculate the volume of emissions for transportation between unreliable and reliable centers with customers, respectively. The amount of environmental pollution between reliable and unreliable centers is calculated using the fifth term. The next four terms represent the volume of pollution in the return reverse flow of the chain. The sixth term describes the volume of emissions caused by transportation between customers and collection centers. The seventh and eighth terms calculate the volume of emissions for transportation between collection centers and recycling centers, respectively. Finally, the ninth term shows the volume of emissions caused by transportation between recovery centers and production centers.

Furthermore, Equation 3 presents the third objective function of the problem, the level of customer satisfaction, which is obtained by minimizing the total dissatisfaction of all customers.

$$Min\ Z_3 = \sum_k \frac{\sum_j \sum_i \sum_r D_k \times YM_{jkr} \times T_{ij}}{D_k} \tag{3}$$

According to Equation 3, the numerator shows the number of products supplied by the customer k, which has been provided by another supplier in the event of a disruption. The denominator also expresses the demand for customer k.

Constraints

After introducing the proposed problem's objectives, the constraints are stated.

$$\sum_m a_{sm} \le B \times Os_s \quad \forall s \tag{4}$$

$$\sum_s \sum_m a_{sm} \times Os_s \ge A \tag{5}$$

$$\sum_j \left(\sum_r YM_{jkr} + YS_{jk} + YR_{jk} \right) = 1 \qquad \forall k \tag{6}$$

$$\sum_j XR_j \ge 1 \tag{7}$$

$$XR_j + XU_j \le 1 \qquad \forall j \tag{8}$$

$$\sum_c Oc_c \ge 1 \tag{9}$$

$$\sum_o Oe_o \ge 1 \tag{10}$$

$$\sum_d Od_d \ge 1 \tag{11}$$

$$\sum_K Y_{kc} \le B \times Oc_c \quad \forall c \tag{12}$$

$$\sum_{c} Zo_{co} \leq B \times Oe_{o} \quad \forall o \tag{13}$$

$$\sum_{d} Zd_{cd} \leq B \times Od_{d} \quad \forall d \tag{14}$$

$$\sum_{k} D_{k} \times \left(\sum_{r} YM_{jkr} + YS_{jk} \right) \leq cap_{j} \times XU_{j} \qquad \forall j \tag{15}$$

$$YR_{jk} \leq XR_{j} \qquad \forall j,k \tag{16}$$

$$T_{ij} \leq \sum_{k} D_{k} \times XR_{i} \qquad \forall i,j \tag{17}$$

$$T_{ij} \leq cap_{j} \times XU_{j} \qquad \forall i,j \tag{18}$$

$$\sum_{j} X_{mj} \leq pcap_{m} \times Op_{m} \qquad \forall m \tag{19}$$

$$\sum_{m} X_{mj} \leq cap_{j} \qquad \forall j \tag{20}$$

$$\sum_{i} T_{ij} + cap_{j} \times \left(\left(1 - \tau_{j} \right) \times XU_{j} \right) \geq \sum_{k} D_{k} \times \left(\sum_{r} YM_{jkr} + YS_{jk} \right) \qquad \forall j \tag{21}$$

$$\sum_{c} QY_{kc} \times Y_{kc} \leq \varepsilon_{k} \times D_{k} \quad \forall k \tag{22}$$

$$\sum_{k} QY_{kc} = \sum_{o} QZo_{co} \times Zo_{co} + \sum_{d} QZd_{cd} \times Zd_{cd} \quad \forall c \tag{23}$$

$$\sum_{c} QZo_{co} = \sum_{m} QW_{om} \times W_{om} \quad \forall o \tag{24}$$

$$Os_{s}, Op_{m}, Oc_{c}, Oe_{o}, Od_{d}, XU_{j}, XR_{j}, YR_{jk}, YS_{jk}, YM_{jkr}, Y_{kc}, Zo_{co}, Zd_{cd}, W_{om} \in \{0,1\} \tag{25}$$

$$a_{sm}, Q_{m}, X_{mj}, QY_{kc}, QZo_{co}, QZd_{cd}, QW_{om}, T_{ij} \geq 0 \tag{26}$$

Constraint (4) states that the required raw materials are procured from a supplier if that supply center is reopened. Constraint (5) expresses that the total raw material transferred to the production centers is at least equal to the total amount of required raw material for producing the products. Constraint (6) enforces that each customer is allocated to only one distribution center and one transport mode. This means that a customer is either assigned to a reliable distribution center or an unreliable distribution center with two modes of safe and unsafe transportation. Constraint (7) guarantees that the proposed supply chain network includes at least one reliable distribution center. Constraint (8) states that if a distribution center is reopened, it is either reliable or unreliable. Constraints (9) to (11) state that at least one collection, recovery, and disposal center must be established, respectively. Constraints (12) indicate that returned products are transported from customers to the collection center if only that center has been established. Constraints (13) and (14) express those products are transported from collection centers to a recovery or disposal center once that center has been set up. Constraint (15) represents that the customer demand assigned to an unreliable distribution center should not exceed the center capacity if it is reopened. Constraint (16) states that a customer can be assigned to a reliable center if only that center is reopened. Constraint (17) expresses that when a disruption happens, the products are transferred from the reliable center i to the unreliable one j if the reliable center i is reopened. Constraint (18) states that in the event of a disruption, the products are transferred from the reliable center i to the unreliable center j if the unreliable center i is reopened. Constraint (19) ensures that the total quantity of products that are transferred from the production center m to the distribution centers should not exceed the production center capacity if it is reopened. Constraint (20) indicates that the number of products sent from the production centers to the distribution center j should not exceed the capacity of that distribution center. Constraint (21) states that for each unreliable center j, the total products transferred from the reliable center j and the total available capacity in case of disruption shall not be less than the total demand of the customers allocated to that center. Constraint (22) ensures that the quantity of returned products to the collection centers does not exceed a certain value. Constraint (23) guarantees that the quantity of products received by each collection center is equal to the number of products sent by that center to the recovery and disposal centers. Constraint (24) guarantees that the quantity of products received by each recovery center is equal to its output to the production center equations. Finally, constraints (25) and (26) show the binary and integer variables of the problem, respectively.

IV. PROPOSED SOLVING APPROACHES

A. ε-constraint

In order to solve multi-objective problems, various methods are developed. In this study, an ε-constraint approach is used to obtain a Pareto solution for the proposed model. In this method, an objective is considered as the main goal, and others are transferred to constraint (Mavrotas, 2009). The number of the solution generated can be controlled in this method while it is impossible for other ones. Considering the different value of epsilon, various solutions can be obtained. For the proposed problem, the ε-constraint method is employed through Equation (27).

$$\begin{aligned} & Min\ f1(x) \\ & x \in X \\ & f2(x) \le \varepsilon_2 \\ & \dots \\ & fn(x) \le \varepsilon_n \end{aligned} \tag{27}$$

The ε-constraint steps are as follows:

1. Considering one of the objectives as the main objective function,
2. Based on each objective function, the problem is solved. Then, the optimal objective functions values are obtained.
3. The difference between the two optimal values of the second objective function is divided into several pre-determined parts. A table of values $\varepsilon_2, ..., \varepsilon_n$ is then generated.
4. The problem is solved by the main objective function and $\varepsilon_2, ..., \varepsilon_n$,
5. Pareto solutions are reported.

B. Non-dominated genetic algorithm

In this study, in addition to presenting a mixed-integer multi-objective programming model, an NSGA-II is also developed. Therefore, in this section, the implementation of the algorithm, operators, and generation of solutions are explained.

To transform an initial solution to a chromosome, the chromosome must show the decisions separately for each level of the supply chain. For instance, facility location and the volume of distribution between different levels of the supply chain are to be considered in the chromosome. For this purpose, the chromosome consists of two parts. The first part represents the locations and the second part specifies the volume of distribution of products. In the first part, the values are between 0 and 1 to generate more various chromosomes. In each cell, if the value is more than .05, the facility is established, otherwise it is not. In the second part, the values are between 0 and 1, which shows the percentage of products sent from one origin to a specific destination. It is noteworthy that the second part is interpreted based on the result obtained from the first part. In other words, according to the located facilities in the first part, the distribution percentage of products located facilities is determined in the second part. This structure is repeated for all levels of the supply chain and all periods.

For example, for the level between the distribution center and the customer in a particular period, the chromosome is shown in Figure 2. In this example, there are three distribution centers and five customers.

<table>
<tr><th colspan="2">Part 1</th><th colspan="2">0.41</th><th colspan="2">0.72</th><th>0.93</th></tr>
<tr><td rowspan="4">Part 2</td><td>Customer / Distribution Center</td><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td></tr>
<tr><td>1</td><td>0.61</td><td>0.29</td><td>0.43</td><td>0.27</td><td>0.35</td></tr>
<tr><td>2</td><td>0.42</td><td>0.73</td><td>0.28</td><td>0.34</td><td>0.19</td></tr>
<tr><td>3</td><td>0.38</td><td>0.91</td><td>0.73</td><td>0.58</td><td>0.39</td></tr>
</table>

Figure 2. An example of chromosome

According to Figure 2, distribution centers 2 and 3 are established because the value generated for these two centers was more than 0.5. The percentage of distribution from distribution centers 2 and 3 can be normalized to determine the amount of demand. The normalization formula is shown in Equation (28).

$$r_i = \frac{x_i}{\sum_{i=1}^{n} x_i} \tag{28}$$

Where x_i is the value of center i, n the number of centers selected, and r_i is the normalized value of the center i. Therefore, the interpretation of the chromosome is presented in Figure 3.

Part 1		0		1		1
Part 2	***Customer*** / ***Distribution Center***	1	2	3	4	5
	1	0	0	0	0	0
	2	0.52	0.44	0.27	0.37	0.32
	3	0.48	0.56	0.73	0.63	0.68

Figure 3. Interpretation of chromosome

After generating the initial population, their fitness function is calculated. In this study, the fitness functions of the algorithm are as same as the objective functions of the problem. The NSGA-II steps are shown in Figure 4.

```
Procedure NSGA-II
  Input: N', g, f_k(X) > N' members evolved g generations to solve f_k(X)
  Initialize Population P';
  Generate random population - size N';
  Evaluate Objectives Values;
  Assign Rank (level) based on Pareto - sort;
  Generate Child Population;
     Binary Tournament Selection;
     Recombination and Mutation;
  for i = 1 to g do
     for each Parent and Child in Population do
         Assign Rank (level) based on Pareto - sort;
         Generate sets of nondominated solutions;
         Determine Crowding distance;
         Loop (inside) by adding solutions to next generation starting from
         the first front until N' individuals;
     end
     Select points on the lower front with high crowding distance;
     Create next generation;
        Binary Tournament Selection;
        Recombination and Mutation;
  end
```

Figure 4. Pseudocode of NSGA-II (Coello et al. 2007)

V. COMPUTATIONAL RESULTS

In this section, computational results are presented based on the evaluation of the performance of the proposed model as well as the proposed solution method.

A. Proposed model validation

To evaluate the proposed mathematical model and prove its efficiency and accuracy, the model has been implemented in GAMS programming software. In Table II, the features of the sample problem are presented. Also, in Table III, the demand of customers is given.

Table II. Sample problem

Indices	*Definition*	*Number*
s	Supply center	2
m	Production center	3
j	Distribution center	3
k	Customers	4
c	Collection center	2
o	Recovery center	2
d	Disposal center	1
r	Unsafe transport mode between distribution centers and customers	2

Table III. Demand of customers

Customers	*Demand*
1	150
2	260
3	210
4	360

In addition, the cost of transportation between reliable distribution centers and unreliable distribution centers is shown in Table III and Table IV.

Table IV. Transportation cost between reliable and unreliable distribution centers (UC_{ij}) (*100)

Reliable distribution center	*Unreliable distribution center*		
	1	*2*	*3*
1	-	14	17
2	11	-	16
3	13	16	-

According to Table V, the other input parameters of the problem are randomly generated based on the uniform distribution.

In this study, an MINLP model is developed for the proposed multi-objective green closed-loop supply chain problem. Since the proposed model contains three objectives, an approach must be employed by which the best solution is obtained, taking into account all three objectives simultaneously. The ε-constraint method is one of the most practical approaches for solving multi-objective problems. This method has been implemented in GAMS software. In this method, each of the objective functions is first optimized separately. Table VI shows the values of each of the objective functions in the two models. Clearly, each of the objective functions has the lowest possible value when they are minimized separately, which indicates the correct operation of the proposed model.

In Table VI, the minimum value of the first and second objective functions are 61515 and 40012, respectively. While in the second model, these values are 84675 and 33711, respectively. Moreover, the best value of the third objective function was zero. In other words, 0 shows other centers totally cover that remaining amount of customers' demands caused by disruption.

According to the obtained values and based on the ε-constraint approach, several points are selected between the upper and lower bound obtained for each of the objective functions, and the new problem is solved. In this study, the first objective function is considered as the main objective, and the second objective function is considered as a constraint.

Table V. Parameter of the problem

Parameter	*Value*	*Parameter*	*Value*
tcd_{cd}	$\sim U(8,20)$	sm_m	$\sim U(900,2000)$
tco_{om}	$\sim U(10,20)$	sc_c	$\sim U(1500,2500)$
$pcap_m$	$\sim U(500,1000)$	so_o	$\sim U(1500,2500)$
cap_j	$\sim U(500,1000)$	sd_d	$\sim U(1500,2000)$
τ_j	$\sim U(0.3,0.5)$	pc_m	$\sim U(7,20)$
q_j	$\sim U(0.35,0.6)$	p_m	$\sim U(10,15)$
π_{jkr}	$\sim U(0.1,0.5)$	ope_o	$\sim U(10,25)$
ε_k	$\sim U(0.4,.6)$	opd_d	$\sim U(10,20)$
GHs_{sm}	$\sim U(10,20)$	fc_s	$\sim U(1600,2200)$
GHm_{mj}	$\sim U(10,20)$	fU_j	$\sim U(1600,2500)$
GHu_{jk}	$\sim U(10,20)$	fR_j	$\sim U(1800,2800)$
GHr_{jk}	$\sim U(10,20)$	stc_{sm}	$\sim U(5,15)$
GH_{ij}	$\sim U(10,20)$	tc_{mj}	$\sim U(5,15)$
GHk_{kc}	$\sim U(10,20)$	dr_{jk}	$\sim U(5,20)$
GHc_{co}	$\sim U(10,20)$	dp_{jk}	$\sim U(5,20)$
GHd_{cd}	$\sim U(10,20)$	db_{jk}	$\sim U(5,20)$

Continue Table V. Parameter of the problem

Parameter	*Value*	*Parameter*	*Value*
GHo_{om}	$\sim U(10,20)$	e_{jkr}	$\sim U(5,20)$
A	$\sim U(100,500)$	tck_{kc}	$\sim U(7,20)$
pf	$\sim U(60,80)$	tcc_{co}	$\sim U(8,20)$

Table VI. Value of objectives

(Z_3)	(Z_2)	(Z_1)	*OBJ* / *Minimization*
0	40012	61515	Z_1^*
0	33711	84675	Z_2^*
0	37424	72305	Z_3^*

Accordingly, the interval for the second objective function is divided into 8 parts (points) and the problem is solved for each of these values. Table VII shows the values obtained from solving the problem.

Table VII. Obtained Pareto solutions by GAMS

Value of Objectives								*Obj*
-	-	-	63105	65133	65421	70924	-	Z_1^*
40012	39000	38000	36189	36000	35000	34000	33711	Z_2

As presented in Table 7, the solution was obtained in 4 points, and there was no integer solution for the rest of the points. Therefore, the above problem has four Pareto solutions, which are also shown in Figure 5.

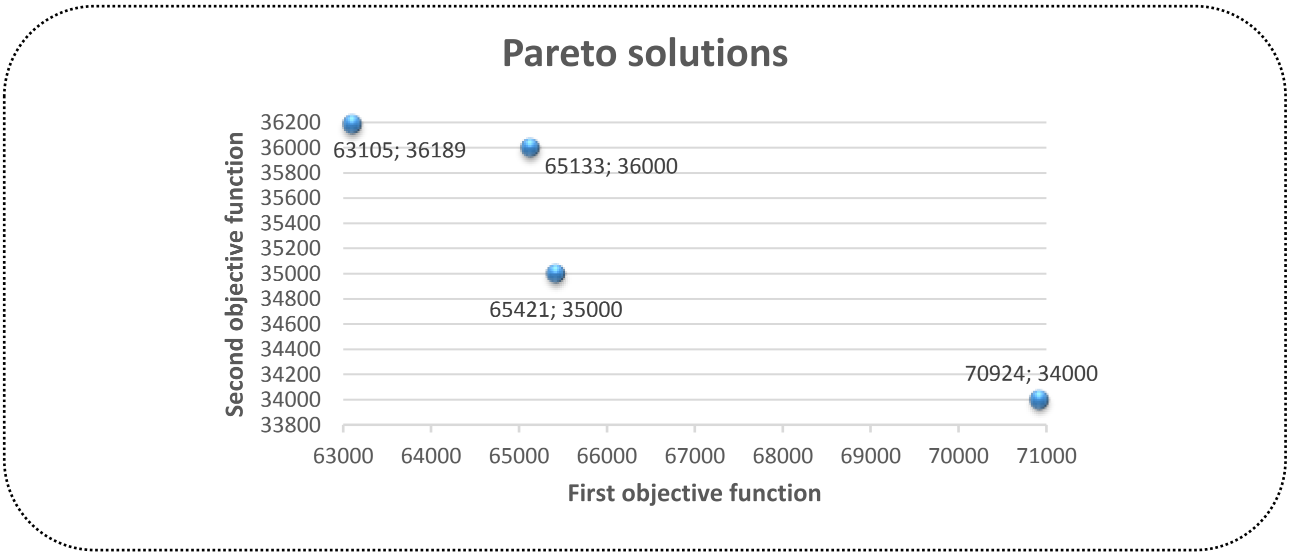

Figure 5. Obtained Pareto solutions by the exact method

B. Proposed algorithm results

The NSGA-II parameters setting is presented in this section. In this study, the Taguchi test design method in MINITAB software was used to adjust the parameters of the proposed genetic algorithm, including initial population (IP), crossover rate (CR), mutation rate (MR), and number of iteration (IT) (Krajčovič et al., 2019). The values of the genetic algorithm are considered in three levels, according to Table VIII.

Table VIII. NSGA-II parameters values

Parameter		***Value***	
IP	70	150	200
IT	150	300	500
CR	0.75	0.85	0.95
MR	0.006	0.009	0.01

In order to evaluate the performance of the proposed genetic algorithm, according to Eq. (29), the relative deviation percentage (RPD) method has been used as the difference criterion (GAP).

$$GAP = \left(\frac{alg_{sol} - best_{sol}}{best_{sol}}\right) \times 100 \tag{29}$$

Where alg_{sol} is objective function value obtained from different combinations of parameters value and $best_{sol}$ is the best one. Different scenarios were obtained by combining different values of NSGA-II algorithm parameters, and the results are reported in Table IX.

Table IX. Results obtained by Taguchi test

Scenario	***IP***	***CR***	***MR***	***IT***	***GAP***
1	70	0.75	0.006	150	0.5032
2	70	0.85	0.009	300	0.1259
3	70	0.95	0.01	500	0.7419
4	150	0.75	0.009	500	0.6635
5	150	0.85	0.01	150	0.4917
6	150	0.95	0.006	300	0.0045
7	200	0.75	0.01	300	0.7124
8	200	0.85	0.006	500	0.7280
9	200	0.95	0.009	300	0.2942

According to Table IX, three values of 70, 150, and 200 for population size, three values of 0.75, 0.85, and 0.95 for intersection rate, three values of 0.006, 0.009, and 0.01 for jump rate, and finally three values of 150, 300 and 500 for the number of repetitions Considered and reviewed a total of 9 cases. It should be noted that each of these cases has been resolved ten times and the mean values of the difference have been reported. Figure 6 also shows the analysis of the Taguchi method for setting the parameters of the proposed genetic algorithm. As can be seen in the diagram at the top left, the effect value of the mean base game for the population size was the lowest; hence the value 200 is selected for the population size. Accordingly, the values of 300, 0.01, and 0.85 have been selected as the best values for the number of repetitions, jump rate, and intersection, respectively.

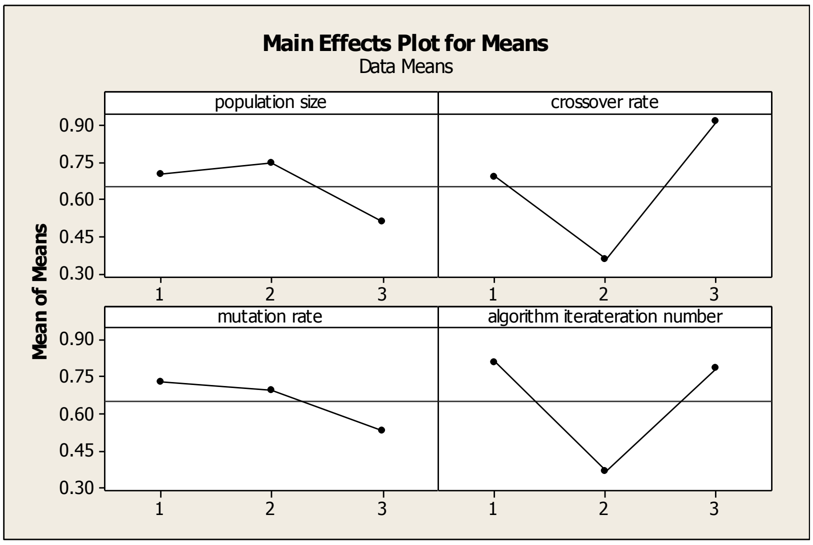

Figure 6. Mean effects plot

The objective functions value obtained by NSGA-II and the ε-constraint method is reported in Table X to validate the proposed algorithm.

Table X. Computational results

Solution No.	***NSGA-II***		***ε-constraint***		GAP (%)
	Obj. 1	***Obj. 2***	***Obj. 1***	***Obj. 2***	
1	70953	34100	70924	34000	0.32
2	65427	35050	65421	35000	0.27
3	65141	36090	65133	36000	0.22
4	63115	36195	63105	36189	0.18

Moreover, the gap between the two methods is reported. It can be seen that the maximum difference is % 0.32, which is near to zero. In other words, there is not any significant difference between the solutions obtained by the two approaches. In the following, four sample problems are generated in the medium and large-sized to evaluate the performance and efficiency of the proposed algorithm in comparison with the exact method. Table XI indicates the size of sample problems.

For a more precise validation of the proposed algorithm and its capability to identify the optimal Pareto front, four criteria specific to multi-objective algorithms are utilized. For this purpose, the four criteria are considered where the first, second, and third columns show the mean ideal distance (MID) measure, while diversity metric (DM) measure indicates in the next two columns. Moreover, space metric (SM), and the number of Pareto solutions (NPS) are presented in the next columns. Then, according to the values of these criteria, the performance of the proposed algorithms is evaluated. The better performance of the algorithm is due to the higher value of DM, lower value of MID, lower value of SM, and higher value of NPS (Sadeghi et al., 2015). The values of criteria calculated for the problems are presented in Table XII.

Table XI. The indices for the sample instances in medium and large-sized

Indices	*P1*	*P2*	*P3*	*P4*
Suppliers	5	10	20	30
Production centers	5	10	15	25
Distribution centers	5	10	15	30
Customers	8	15	25	40
Collection centers	3	7	10	12
Recovery centers	3	7	10	12
Disposal centers	3	7	10	12

Table XII. Two algorithms' criteria average value

Criteria	*DM*		*MID*		*SM*		*NPS*	
Method / *Problem*	*EC*	*NSGA-II*	*EC*	*NSGA-II*	*EC*	*NSGA-II*	*EC*	*NSGA-II*
1	1.04	1.13	0.75	0.83	1.06	0.92	3	5
2	1.11	1.07	1.2	1.11	1.13	1.05	3	9
3	-	0.76	-	0.78	-	0.68	-	16
4	-	1.03	-	1.25	-	1.24	-	21

According to Table XII, the proposed NSGA-II algorithm performs closely to the exact algorithm, and as a result, it has a high efficiency to find near-optimal solutions. In this regard, the proposed NSGA-II algorithm can be employed to solve large-size problems. More specifically, the NSGA-II algorithm performs much better than the EC in terms of Diversity criteria. This means that the NSGA-II algorithm is capable of generating Pareto fronts with a wider range of possible solutions.

In terms of MID, the NSGA-II algorithm also performs more efficiently rather than EC. That is, in this algorithm, the distance from the ideal point at any solution is less than the EC method. Additionally, in terms of Space Metric, the performance of the NSGA-II algorithm has been much more appropriate, and it has produced a more uniform front than EC. Additionally, in terms of Space Metric, the performance of the NSGA-II algorithm has been much more appropriate, and it has produced a more uniform front than EC. Besides, the NSGA-II algorithm has always managed to find more Pareto solutions.

In the following, the tradeoff between different objective functions is done for the fourth sample problem for both proposed methods. Figures 7 to 9 show the tradeoff between every two objective functions for both methods. The blue point shows the solution obtained by the exact method, while the red one indicates the algorithm solutions.

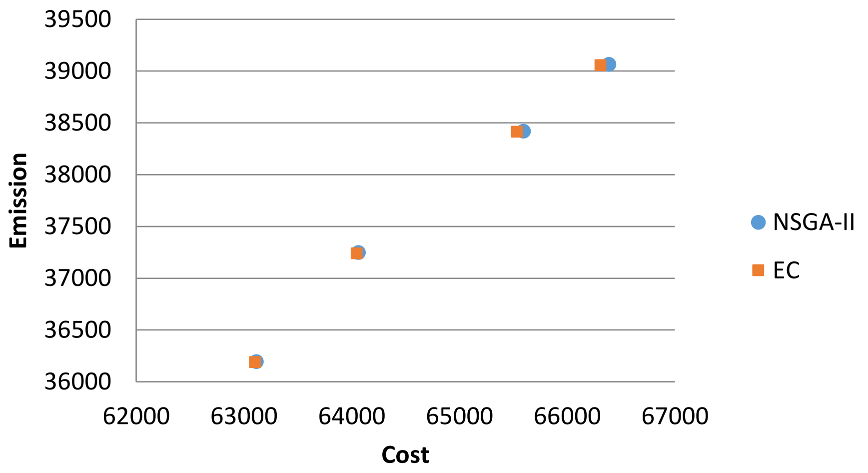

Figure 7. Cost-Emission tradeoff

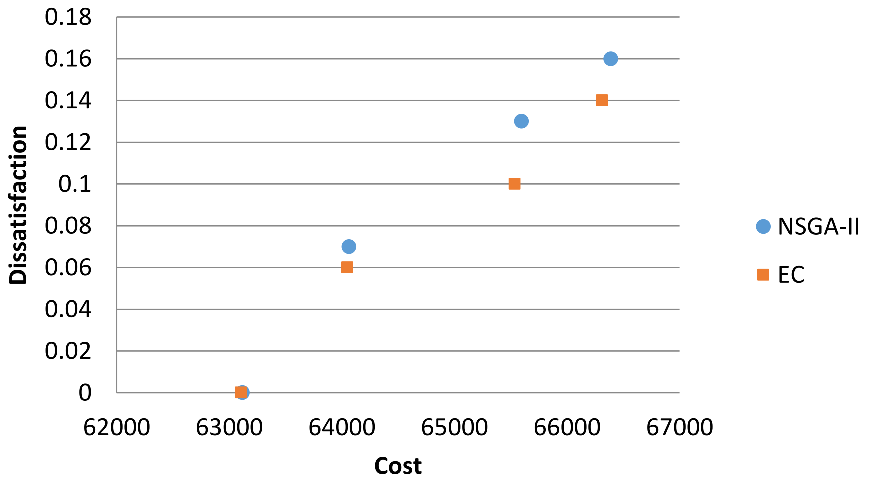

Figure 8. Cost-Dissatisfaction tradeoff

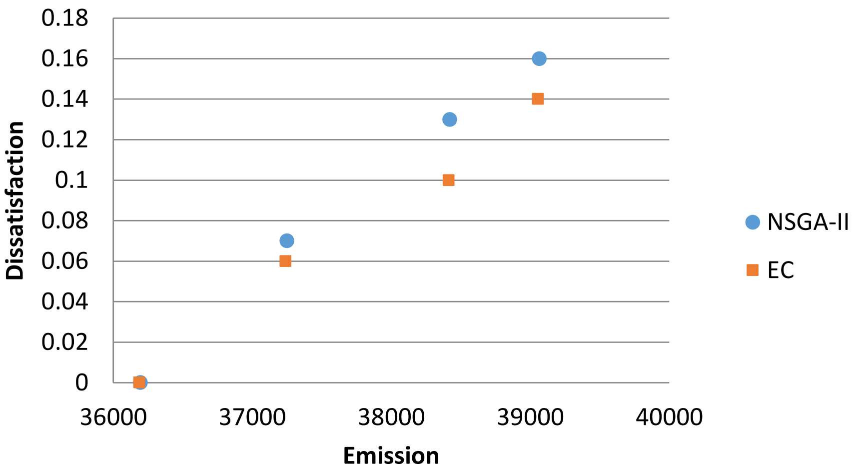

Figure 9. Emission-Dissatisfaction tradeoff

C. Sensitivity analysis

Furthermore, sensitivity analysis of important parameters affected on objective function is done. As mentioned above, since the third objective function value was 0, the sensitivity analysis is only done on the first and second objective functions. Firstly, the impact of disruption possibility on each objective function is investigated separately. Its amount varies from -20 to +20 percent. Figure 10 shows the variation of the objective function according to the disruption possibility parameter.

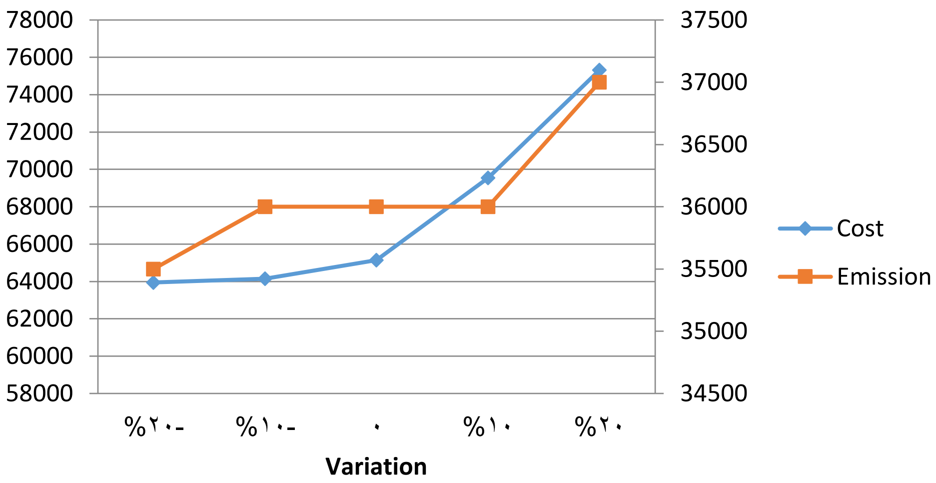

Figure 10. Disruption variation effect on objective functions

As shown in Figure 10, increasing the amount of disruption possibility causes to increase the total cost exponentially while the emission amount has less effectiveness than the possibility of disruption variation. The customer demand is also analyzed to investigate its effect on each objective function. To do this end, its amount is changed from -20% to

20%. Figure 11 depicts the trend of objective function according to demand variation. As shown in Figure 11, increasing the amount of demand causes to increase in both the total cost and emission amount.

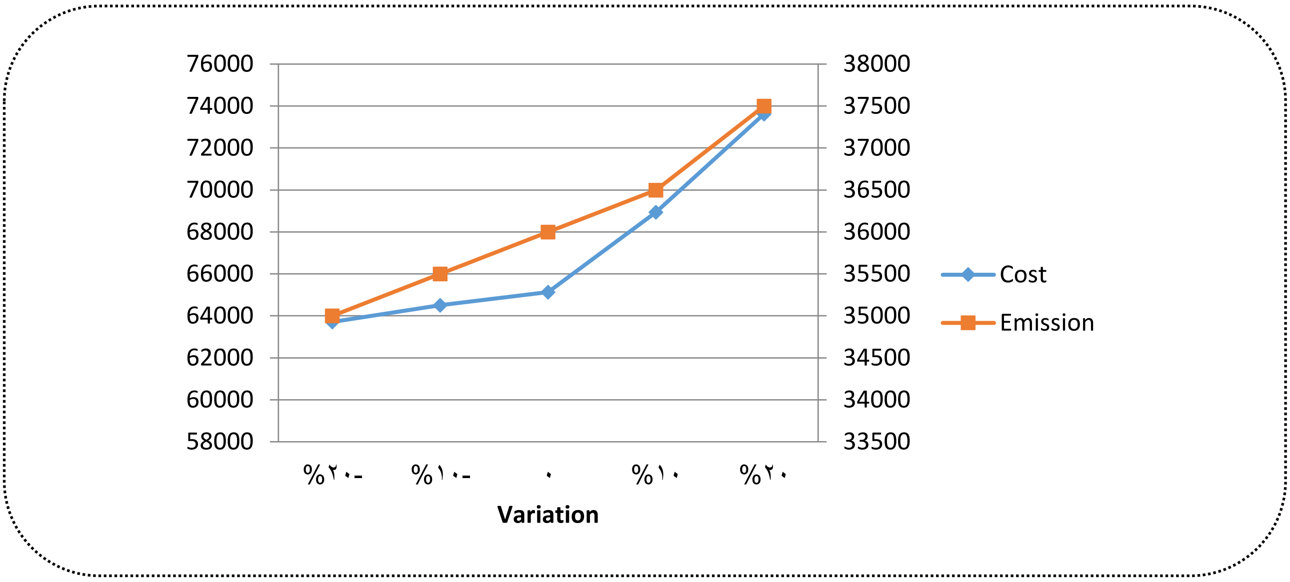

Figure 11. Demand variation effect on objective functions

As mentioned before, managers face some challenges such as determining the number of products shipped among various centers, customer demand, and location-allocation. The proposed model helps managers to decide about them with minimum possible costs and emissions. As a bi-objective problem is considered, a Pareto solution frontier is obtained where managers, based on their priority, select the suitable one.

VI. CONCLUSION AND FUTURE WORKS

In this paper, a green closed-loop supply chain was developed considering the disruptions in the centers. The main contribution of the paper is the design of a support decision system for planning the supply, production, and distribution of products taking into account the main assumptions of the real world, including the possibility of disrupting the distribution of products. The objectives of the problem include minimizing the total cost of the network, minimizing the total volume of emissions at the chain level, and maximizing customer satisfaction. Moreover, the GAMS software and ε-constraint method were used as the exact method to solve the problem and prove the efficiency and validation of the proposed model. For further study, the future suggestions are to introduce the concepts of reliability of facilities, considering data uncertainty, as well as the use of other meta-heuristic algorithms for solving the large size problems.

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