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A Multi-Objective Model for Green Closed-Loop Supply Chain Design by Handling Uncertainties inEffective Parameters

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***Abstract** – The process of designing and redesigning supply chain networks is subject to multiple uncertainties. Given the growing environmental pollution and global warming caused by societies' industrialization, this process can be completed when environmental considerations are also taken into account in the decisions. In this study, an integrated four-level closed-loop supply chain network, including factories, warehouses, customers, and disassembly centers (DCs) is designed to fulfill environmental objectives in addition to economic ones. The reverse flow, including recycling and reprocessing the waste products, is considered to increase production efficiency. Also, the different transportation modes between facilities, proportional to their cost and greenhouse gas emissions, are taken into account in the decisions. A random cost function and chance constraints are presented firstly to handle the uncertainties in different parameters. After defining the random constraints using the chance-constraint programming approach, a deterministic three-objective model is presented. The developed model is solved using the GAMS software and the goal attainment (GA) method. Also, the effect of the priority of the goal, uncertain parameters, and confidence level of chance constraints on objective function values has been carefully evaluated using different numerical examples.*

***Keywords**– Green Closed-loop supply chain network design, Stochastic programming, Chance-constrained programming, Goal-attainment.*

I. INTRODUCTION

Nowadays, organizations and companies' structure is being studied in the form of supply chain networks due to the globalization and industrialization of societies. The performance of all supply chain subsets, including suppliers, factories, warehouses, retailers, customers, and DCs is contingent upon the networks' optimal design. Network design is a process involving decision making related to strategic (e.g., location, capacity, etc.), tactical (e.g., allocation, planning, etc.), and operational (e.g., order size, inventory, etc.) variables (Chopra and Meindl, 2007). The SC design goal can be defined as receiving raw materials, changing them into final goods, and dispatching those final goods to the customer zones (Babazadeh et al., 2013).

The growing concerns about environmental pollutions and government regulations to control greenhouse gas emissions, along with an increasing competition to optimize network performance and reduce waste, have encouraged

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researchers to design and reconstruct chains for the realization of environmental goals and sustainability. Sustainability implementation in the supply chain structure is a critical factor that exerts pressure on the organizations to reduce their negative environmental impacts, thereby boosting social and economic benefits (Zailani et al., 2012).

In addition to considering economic and environmental objectives, network structure efficiency requires controlling uncertainties in the most useful parameters. There are two approaches for handling uncertainties: 1- selecting the appropriate method of modeling uncertainties, and 2- choosing a more comprehensive range of uncertain parameters. To better cope with uncertainties, researchers have assumed various parameters including demand, supply, costs, processing time, facility capacity, etc. (Azaron et al., 2008, Cardona-Valdes et al., 2011, Song et al., 2014) . Choosing the most effective and appropriate parameters in the network design, compared to the uncertainty modeling method, is a subject that has been less studied in the previous research.

This paper aims to present a two-objective stochastic mixed-integer linear programming model and transform it into a three-objective nonlinear integer programming for designing a green closed-loop supply chain network. In order to handle the uncertainties in the mathematical model, a wide range of parameters including are assumed with uncertainty as follows: the costs of production, reproduction, maintenance, collection, disassembly, and transportation, the minimum percentage of the product units to be disposed to be collected from a customer, and the minimum percentage of the units of product to be dismantled to be shipped from a DC.

Different sections of this study are categorized in the following way. Section2 gives an overview of past research and the existing literature gaps. Section3 presents goals, assumptions, research applications, and mathematical models and introduces sets, parameters, and decision variables. Section 4 describes the proposed multi-objective decision-making methodology. Finally, section 4 presents some numerical examples of goal attainment and sensitivity analysis for the fundamental parameters.

II. LITERATURE REVIEW

Researchers have taken different approaches to design supply chain networks. Some have designed SCs using single-objective or multi-objective planning approaches. Alshamsi and Diabat (2015) have, for example, formulated a single-objective mixed-integer linear programming model for the design of a reverse logistics system. Their model's most important innovation has been deciding on different options, including internal fleet transport or outsourcing between different facilities. Also, Altiparmak et al. (2006) have proposed a mixed-integer nonlinear linear programming model for a four-level supply chain design using the multi-objective programming approach. Their objective functions have been to minimize total network costs, maximize customer service level, and increase balance in disassembly centers. They have used a new method based on a genetic algorithm, creating a Pareto front. Some scholars have also considered the reverse flow in their SCs to control the waste product. Ozceylan et al. (2016) have, for instance, presented a single-objective model for designing a closed-loop supply chain network to fulfill the requirements of the existing regulations in some countries regarding the necessity of recycling end-of-life products. The performance of the proposed model has been investigated in a car factory under different scenarios. Haddadsisakht and Ryan (2018) have also proposed a three-stage stochastic programming model for designing a closed-loop supply chain network. The returned products' demand and quantity have been considered along with the possible scenarios in their model. The growth of environmental pollutants and customers' demand to produce environmentally friendly products have encouraged many researchers to design sustainable and green networks. In this regard, Nurjanni et al. (2016) have developed new modeling for the green closed-loop supply chain design. They have considered both economic and environmental objective functions for the network design. In their multi-objective model, locating facilities and establishing flow and various transportation modes between components were considered. They have used three different scalability methods to convert a two-objective model to a single-objective one and create an optimal Pareto set. Mardan et al. (2019) have also presented a two-objective model for designing a multi-period and multi-product closed-loop green supply chain network. They have used an accelerated Benders decomposition algorithm to solve the developed model. Further, Devika et al. (2014) have formulated the social dimensions of sustainability and economic and environmental dimensions in the closed-loop supply chain network with six echelons. They have solved the mixed-integer linear multi-objective model with three hybrid metaheuristic methods based on the imperialist competitive algorithms and the variable neighborhood search. Researchers have examined handling uncertainties in decision making in the design of both traditional and green networks. Some of the uncertainty modeling approaches have been based on the absence of historical data on uncertain parameters. In this regard, Mohammed and Wang (2017) have designed a green open-loop supply chain using fuzzy programming. They have considered the Epsilon constraint, global criteria, and goal-programming methods to solve the model and used the max-min method to select the best solution. On the other hand, Bera et al. (2020) have developed a multi-objective model for designing a green supply chain network by considering uncertain parameters as fuzzy triangular numbers. They have applied a new approach to converting the multi-objective model to the single-objective one. Other approaches considered to deal with uncertainties have been based on historical data for uncertain parameters. Pasandideh et al. (2014), for instance, have proposed a mixed-integer nonlinear multi-objective model for designing a multi-period multi-product three-echelon supply chain network. They have used chance-constrained programming to handle uncertainty. Reazaee et al. (2017) have also designed a four-level green open-loop supply chain network. They have developed a two-stage stochastic scenario-based programming model to control the uncertainties in strategic and tactical decisions. Their case study has been conducted to evaluate the model's efficiency on the supply chain of an office furniture manufacturer in Australia. Heidari-Fathian and Pasandideh (2018) have also developed a multi-objective mixed-integer programming model for designing a green blood supply chain network whose objectives were to minimize total costs and environmental impacts. They have applied the Lagrangian relaxation algorithm to solve the robust model. Further, Yavari and Geraeli (2019) have formulated a multi-objective mixed-integer linear programming model to design a multi-period multi-product green closed-loop supply chain network produc1e perishable products. They considered the demand, rate, and quality of the returned products with uncertainty and used a robust optimization approach for modeling.

This paper designs a novel green closed-loop supply chain network by using a mixed-integer nonlinear three-objective programming model. The design process involves strategic decisions to discretely locate facilities and tactical decisions to determine the flow rate and transportation mode between facilities. It should be noted that modeling a wide range of useful non-deterministic parameters for the problem improves the handle of uncertainties in decision making. The GA method is used to solve the model, and sensitivity analysis is carefully performed on different sensitive parameters.

To summarize, the innovative features of the paper, as compared to other studies, are noted below:

1. A novel mathematical model is presented for designing a green supply chain network with both reverse and direct flow. Strategic and tactical decision variables are considered in both direct and reverse flows.
2. The cost and greenhouse gas emissions of producing, reproducing, collecting, handling, disassembling, and transportation are considered in the decisions.
3. For the first time, novel parameters including all cost parameters, the minimum percentage of the waste products to be collected from customers, and the minimum percentage of the products returned to the factory for reproduction are assumed to be uncertain.

4. The developed model considers the concepts of greenness and copes with uncertainty by using chance-constrained programming.
5. Past research has examined two aspects of considering different assumptions in network design and the types of uncertain parameters.

III. PROBLEM DEFINITION

Fig. I shows a schematic display of the green supply chain, including factories, warehouses, customers, and DCs, along with different transportation modes. The flow of network is divided into three categories: 1. direct flow of the intact products from factory to customer, 2. the reverse flow of the End of Life (EOL) products passed from the customer to the disassembly centers and returned to the direct flow, and 3. the flow of the End of Use (EOU) products returns to the mainstream after collecting from customers and recycling.

Table I. Model assumptions related to the supply chain network design in the previous studies

Scholars	***Flow***	***Type of the model***	***Objectives***	***Greenness or sustainability***	***Uncertainty modeling method***	***Determining transportation modes***
Kamali et al. (2011)	Forward	MILP	Maximizing profits, Minimizing defective products and late deliverables	-	-	-
Pati et al. (2013)	Forward-reverse	MILP	Minimizing the total cost	-	-	-
Ozkir and Basligil (2013)	Reverse	MILP	Maximizing the profit, maximizing the sales price, maximizing customer satisfaction	-	-	-
Pishvaee et al. (2014)	Forward	MILP	Minimizing the costs and the environmental impact, maximizing the social benefits	✓	Possibilistic programming	-
Shaw et al. (2016)	Forward	MILP	Minimizing the total cost and greenhouse gas emissions	✓	-	-
Nurjanni et al. (2016)	Forward-reverse	MILP	Minimizing the total cost and greenhouse gas emissions	✓	-	✓
Tsao et al. (2018)	Forward	MILP	Minimizing the economic costs and environmental impact, maximizing social benefits	✓	Fuzzy programming	-
Fathollahi Fard et al. (2018)	Forward-reverse	MILP	Minimizing the environmental impact and the risk	✓	Stochastic scenario based-based programming	-
Chalmardi and Vallejo (2019)	Forward	MILP	Maximizing the profits, minimizing the greenhouse gas emissions	-	-	-
Fakhrzad and Goodarzian (2019)	Forward-reverse	MINLP	Minimizing the costs and the environmental impacts of the network, maximizing the reliability of the demand delivery	✓	Fuzzy programming	-
Yavari and Geraeli (2019)	Reverse	MILP	Minimizing the costs and the environmental pollutants	✓	Robust optimization	-
Current research	Forward-reverse	MINLP	Minimizing the expected value of cost, the variance of costs, and the environmental impact	✓	Hybrid Possibilistic and chance-constrained programming	✓

Table II. Uncertain modeling methods and uncertain parameters considered in the previous studies

Researchers	*Method of uncertainty modeling*	*Uncertain parameters*
Pasandideh et al. (2014)	Possibilistic programming (chance-constrained programming)	Costs, demand, production and set-up times,
Zeballos et al. (2014)	Multi-stage stochastic scenario-based programming	Demand and quantity of the raw materials supply
Qu et al. (2016)	Robust optimization (based on Monte Carlo simulation)	Structural design parameters (shaping dimensions and positioning dimensions and radius)
Khatami et al. (2016)	stochastic scenario-based programming	Demand and quantity of the returned products
Imran et al. (2018)	Fuzzy programming	product complaints
Haddadsisakht and Ryan (2018)	Three-stage stochastic programming	Demand, the quantity of the returned products, and carbon tax rate
Al-Juboori and Datta (2019)	Multi-objective stochastic programming	heterogeneous hydraulic conductivity
Yavari and Geraeli (2019)	Robust optimization	Demand, rate of return, and quality of the returned products
Trochu et al. (2020)	a two-stage multi-objective stochastic model	quantity of the waste generated and the recycling rates at the collection centers
This paper	Hybrid possibilistic and chance-constrained programming	Production, reproduction, handling, collection, disassembling, shortage and transportation cost, Minimum percentage of the units of product to be disposed to be collected from a customer, the minimum percentage of the units of product to be dismantled to be shipped from a DC

Since cost parameters due to inflation, political conditions, sanctions, etc., are uncertain, the random cost function is presented to design such a network. Also, two chance constraints are presented to handle the inherent uncertainty in the parameters of the return current. Then, an integrated tri-objective mixed integer nonlinear programming model whose first objective function minimizes the expected value of the total costs is provided. The second objective function minimizes the variance of the total costs. The third objective function also minimizes the total carbon dioxide emissions. Some assumptions of the model are as follows:

1. A single product and a single period model
2. The shortage is allowed for all customers.
3. Due to some prior contracts for producing a certain amount of products, customer demand is assumed to be specific.
4. All cost parameters and the minimum percentage of the product units to be disposed and collected from a customer and to be dismantled and shipped from a DC are assumed with uncertainty.
5. There is historical data on stochastic parameters, so a possibilistic programming approach has been used to model the uncertainties.
6. All uncertain parameters are assumed to have a normal distribution with the specified mean and variance.
7. There are different transportation modes between facilities, including air, land, sea, rail, etc.
8. The distance between the facility locations is considered as a straight line. Transportation rates are used to account for different mode network characteristics (tortuosity, no feasible link, etc.). (Giarola et al., 2011)

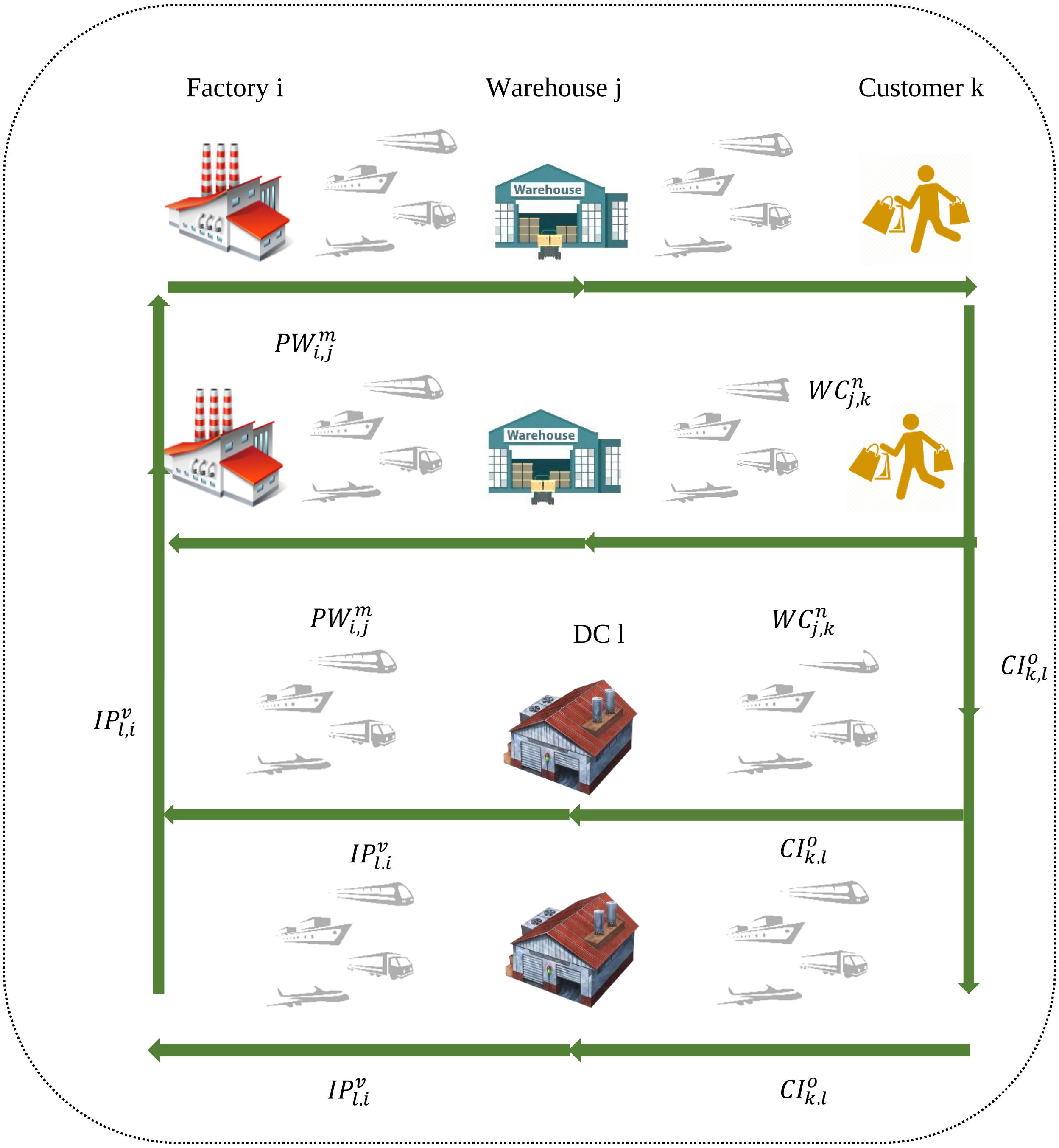

Figure 1. The structure of the communication between the facilities in the green and sustainable supply chain network

Table III. Indicators of the mathematical model

Indexes	***Description***
i	Index for factories (i=1,2,…, |I|)
j	Index for storehouses (j=1,2,…, |J|)
k	Index for customers (k=1,2,…, |K|)

Table III. Indicators of the mathematical model

Indexes	*Description*
l	Index for DCs (l=1,2,…, |L|)
m	Index for transportation options from factories (m=1,2,…, |M|)
n	Index for transportation options from storehouses (n=1,2,…, |N|)
o	Index for transportation options from customers (o=1,2,…, |O|)
v	Index for transportation options from DCs (v=1,2,…, |V|)

Table IV. The defined parameters for modeling

Parameter	*Explanation*
$\widetilde{cp_i}$	Fixed cost for establishing the factory $i \in I$ with the mean μcp_i and the variance σcp_i
$\widetilde{cw_j}$	Fixed cost for establishing the warehouse $j \in J$ with the mean μcw_j and the variance σcw_j
$\widetilde{cd_l}$	Fixed cost for establishing DC $l \in L$ with the mean μcd_l and the variance σcd_l
$\widetilde{c'p_i}$	The unit variable cost for producing a unit product in the factory $i \in I$ with the mean $\mu c'p_i$ and the variance $\sigma c'p_i$
$\widetilde{c'h_j}$	The unit variable cost for handling a unit of product in the warehouse $j \in J$ with the mean $\mu c'h_j$ and the variance $\sigma c'h_j$
$\widetilde{c'c_k}$	The unit variable cost for collecting a unit of product to be disposed of the customer $k \in K$ with the mean $\mu c'c_k$ and the variance $\sigma c'c_k$
$\widetilde{c'd_l}$	The unit variable cost for disassembling a unit of product to be disposed of DC $l \in L$ with the mean $\mu c'd_l$ and the variance $\sigma c'd_l$
$\widetilde{c'r_i}$	The unit variable cost for reproducing a unit product in the factory $i \in I$ with the mean $\mu c'r_i$ and the variance $\sigma c'r_i$
$\widetilde{c'q_k}$	Unit shortage cost for a unit product in the customer k$\in K$ with the mean $\mu c'q_k$ and the variance $\sigma c'q_k$
$\widetilde{c''p_{i,j}^m}$	Unit transportation cost from the factory i to the warehouse j with the transportation mode m with the mean $\mu c''p_{i,j}^m$ and the variance $\sigma c''p_{i,j}^m$
$\widetilde{c''w_{j,k}^n}$	Unit transportation cost from the warehouse j to the customer k with the transportation mode n, the mean $\mu c''w_{j,k}^n$ and the variance $\sigma c''w_{j,k}^n$
$\widetilde{c''c_{k,l}^o}$	Unit transportation cost for collecting the unit of product from the customer k to DC l with the transportation mode o, the mean $\mu c''c_{k,l,}^o$ and the variance $\sigma c''c_{k,l}^o$
$\widetilde{c''d_{l,i}^v}$	Unit transportation cost from DC l to the factory i with the transportation mode v, the mean $\mu c''d_{l,i}^v$, and the variance $\sigma c''d_{l,i}^v$
rp_i	Rate of the released CO2 to produce one unit of product in the factory i
rw_j	Rate of the released CO2 to handle and store one unit of product in the warehouse j
rd_l	Rate of released CO2 to disassemble one unit of product to be disposed of in DC l
rr_i	Rate of the released CO2 to remanufacture one unit of product to be dismantled in factory i

Continue Table IV. The defined parameters for modeling

Parameter	***Explanation***
$r''p_m$	CO2 released by the transportation mode m to forward a unit of product from factory to warehouse for a unit distance
$r''w_n$	CO2 released by the transportation mode n to forward a unit of product from the warehouse to the customer for a unit distance
$r''c_o$	CO2 released by the transportation mode m to collect a unit disposal from the customer to DC for a unit distance
$r''d_v$	CO2 released by the transportation mode v to ship a unit of product to be dismantled from DC to the factory for a unit distance
up_i	The maximum production capacity of the factory i
uw_j	Maximum storage and handling and processing capacity of the warehouse j
ud_l	Maximum disassembly capacity of DC l
ur_i	The maximum reproduction capacity of the factory i
$\alpha p_{i,j}^m$	Transportation rate from the factory i to the storehouse j with the transportation mode m
$\alpha w_{j,k}^n$	Transportation rate from the warehouse j to the customer k with the transportation mode n
$\alpha c_{k,l}^o$	Transportation rate cost for collecting the unit of product from the customer k to DC l with the transportation mode o
$\alpha d_{l,i}^v$	Transportation rate from DC l to the factory i with transportation mode v
$sp_{i,j}$	The distance between factory i and the warehouse j
$sw_{j,k}$	The distance between the warehouse j and the customer k
$sc_{k,l}$	The distance between the customer k and DC l
$sd_{l,i}$	The distance between DC l and the factory i
$\tilde{\gamma}$	The minimum percentage of the units of product to be disposed to be collected from a customer with the mean $\mu\gamma$ and the variance $\sigma\gamma$
$\widetilde{\gamma'}$	The minimum percentage of the units of product to be dismantled to be shipped from a DC with the mean $\mu\gamma'$ and the variance $\sigma\gamma'$
d_k	The demand of the customer k
β	The chance of rejecting a solution that does not satisfy the constraint
$Z_{1-\beta}$	The lower critical point of the standard normal distribution used for a $(1-\beta)\%$ chance constraint on the solution obtained

Table V. Strategical and tactical decision variables of the mathematical model

Decision Variables	*Description*
Fp_i	$\begin{cases} 1 \text{ if the factory i is established} \\ 0 \qquad\qquad \text{o.w} \end{cases}$
Fw_j	$\begin{cases} 1 \text{ if the warehouse j is established} \\ 0 \qquad\qquad \text{o.w} \end{cases}$
Fd_l	$\begin{cases} 1 \text{ if DC l is established} \\ 0 \qquad\qquad \text{o.w} \end{cases}$
$PW_{i,j}^m$	The amount of the unit product shipped from factory i to the warehouse j with the transportation mode m
$WC_{j,k}^n$	The amount of the unit product shipped from the warehouse j to the customer k with the transportation mode n
$CI_{k,l}^0$	The amount of the unit product to be disposed and collected from the customer k to DC l with the transportation mode o
$IP_{l,i}^v$	The amount of the unit product to be dismantled and shipped from DC l to the factory i with the transportation mode v
SH_k	The amount of shortage for customer k

Based on the defined indices, parameters, and decision variables, a stochastic cost objective function for the supply chain network design is proposed, as follows:

$$
\begin{aligned}
min\tilde{Y} = {} & \sum_{i=1}^{I} \widetilde{cp_i}\, Fp_i + \sum_{j=1}^{J} \widetilde{cw_j}\, Fw_j + \sum_{l=1}^{L} \widetilde{cd_l}\, Fd_l + \sum_{i=1}^{I} \widetilde{c'p_i} \sum_{j=1}^{J}\sum_{m=1}^{M} PW_{i,j}^m \\
& + \sum_{j=1}^{J} \widetilde{c'h_j} \sum_{k=1}^{K}\sum_{n=1}^{N} WC_{j,k}^n + \sum_{k=1}^{K} \widetilde{c'c_k} \sum_{k=1}^{K}\sum_{n=1}^{N} WC_{j,k}^n + \sum_{l=1}^{L} \widetilde{c'd_l} \sum_{k=1}^{K}\sum_{o=1}^{O} CI_{k,l}^0 \\
& + \sum_{i=1}^{I} \widetilde{c'r_i} \sum_{l=1}^{L}\sum_{v=1}^{V} IP_{l,i}^v + \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{m=1}^{M} \widetilde{c''p_{i,j}^m}\, PW_{i,j}^m + \sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{n=1}^{N} \widetilde{c''w_{j,k}^n}\, WC_{j,k}^n \\
& + \sum_{k=1}^{K}\sum_{l=1}^{L}\sum_{o=1}^{O} \widetilde{c''c_{k,l}^o}\, CI_{k,l}^0 + \sum_{l=1}^{L}\sum_{i=1}^{I}\sum_{v=1}^{V} \widetilde{c''d_{l,i}^v}\, IP_{l,i}^v + \sum_{k=1}^{K} \widetilde{c'q_k}\; SH_k
\end{aligned}
\tag{1}
$$

The function $\tilde{Y}$ includes the fixed costs of constructing factories, warehouses, and DCs, and the variable costs associated with the production, reproduction, maintenance, collection, disassembly, and transportation between facilities. It is also considered a penalty cost for the customer shortage.

To handle the uncertainties in the cost parameters, the expected value, and variance of the random function $\tilde{Y}$ must be minimized. The function $\tilde{Y}$ has the mean and variance states, as shown in the Eqs. (2), (3):

$$\begin{cases} E(\tilde{Y}) = Z_1 & (2) \\ E(\tilde{Y}) = Z_2 & (3) \end{cases}$$

Following stochastic constraints are provided in Eqs. (4) and (5) to handle the uncertainty of the minimum percentages of the waste products collected from each customer and the minimum percentages of the products transferred from the disassembly centers.

$$p\left\{\sum_{l=1}^{I}\sum_{o=1}^{O} CI_{k,l}^{0} + \gamma SH_k \geq \gamma d_k\right\} \geq 1 - \beta \qquad \forall k \in K \tag{4}$$

$$p\left\{\sum_{i=1}^{I}\sum_{v=1}^{V} IP_{l,i}^{v} \geq \gamma' \sum_{k=1}^{K} CI_{k,l}^{0}\right\} \geq 1 - \beta \qquad \forall l \in L \tag{5}$$

The random functions, $\widetilde{G_1}$ and $\widetilde{G_2}$ are defined for transforming a stochastic form of Eqs (4) and (5) to a deterministic one.

$$\widetilde{G_1} = \sum_{l=1}^{I}\sum_{o=1}^{O} CI_{k,l}^{0} + \gamma SH_k - \gamma d_k \tag{6}$$

$$\widetilde{G_2} = \sum_{i=1}^{I}\sum_{v=1}^{V} IP_{l,i}^{v} - \gamma' \sum_{k=1}^{K} CI_{k,l}^{0} \tag{7}$$

Since each linear combination of normal variables is expected, the standard normal distribution, according to equations 8, 9, 10, 11, 12, and 13, has been used to calculate the definite form of the chance constraints 4 and 5.

$$p\left(\widetilde{G_1} \geq 0\right) \geq 1 - \beta \tag{8}$$

$$p\left(z \geq \frac{0 - \sum_{l=1}^{I}\sum_{o=1}^{O} CI_{k,l}^{0} - \mu\gamma SH_k + \mu\gamma d_k}{\sqrt{\sigma\gamma {SH_k}^2 + \sigma\gamma {d_k}^2}}\right) \geq 1 - \beta \tag{9}$$

$$\frac{0 - \sum_{l=1}^{I}\sum_{o=1}^{O} CI_{k,l}^{0} - \mu\gamma SH_k + \mu\gamma d_k}{\sqrt{\sigma\gamma {SH_k}^2 + \sigma\gamma {d_k}^2}} \leq z_{1-\beta} \tag{10}$$

$$p\left(\widetilde{G_2} \geq 0\right) \geq 1 - \beta \tag{11}$$

$$p\left(z \geq \frac{0-\sum_{i=1}^{I}\sum_{v=1}^{V} IP_{l,i}^{v} + \mu\gamma' \sum_{k=1}^{K} CI_{k,l}^{0}}{\sqrt{\sigma\gamma {SH_k}^2 + \sigma\gamma {d_k}^2}}\right) \geq 1-\beta \tag{12}$$

$$\frac{0-\sum_{i=1}^{I}\sum_{v=1}^{V} IP_{l,i}^{v} + \mu\gamma' \sum_{k=1}^{K} CI_{k,l}^{0}}{\sqrt{\sigma\gamma {SH_k}^2 + \sigma\gamma {d_k}^2}} \leq z_{1-\beta} \tag{13}$$

A nonlinear deterministic three-objective model for the design of the integrated closed-loop supply chain networks is presented, as follows:

$$\begin{aligned} minZ_1 =& \sum_{i=1}^{I} \mu cp_i\, Fp_i + \sum_{j=1}^{J} \mu cw_j\, Fw_j + \sum_{l=1}^{L} \mu cd_l\, Fd_l + \sum_{i=1}^{I} \mu c' p_i \sum_{j=1}^{J}\sum_{m=1}^{M} PW_{i,j}^{m} \\ &+ \sum_{j=1}^{J} \mu c' h_j \sum_{k=1}^{K}\sum_{n=1}^{N} WC_{j,k}^{n} + \sum_{k=1}^{K} \mu c' c_k \sum_{k=1}^{K}\sum_{n=1}^{N} WC_{j,k}^{n} + \sum_{l=1}^{L} \mu c' d_l \sum_{k=1}^{K}\sum_{o=1}^{O} CI_{k,l}^{0} \\ &+ \sum_{i=1}^{I} \mu c' r_i \sum_{l=1}^{L}\sum_{v=1}^{V} IP_{l,i}^{v} + \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{m=1}^{M} \mu c'' p_{i,j}^{m}\, PW_{i,j}^{m} + \sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{n=1}^{N} \mu c'' w_{j,k}^{n}\, WC_{j,k}^{n} \\ &+ \sum_{k=1}^{K}\sum_{l=1}^{L}\sum_{o=1}^{O} \mu c'' c_{k,l}^{o}\, CI_{k,l}^{0} + \sum_{l=1}^{L}\sum_{i=1}^{I}\sum_{v=1}^{V} \mu c'' d_{l,i}^{v}\, IP_{l,i}^{v} + \sum_{k=1}^{K} \mu c' q_k\ SH_k \end{aligned} \tag{4}$$

$$\begin{aligned} minZ_2 =& \sum_{i=1}^{I} \sigma cp_i\, {Fp_i}^2 + \sum_{j=1}^{J} \sigma cw_j\, {Fw_j}^2 + \sum_{l=1}^{L} \sigma cd_l\, {Fd_l}^2 \\ &+ \sum_{i=1}^{I} \sigma c' p_i \sum_{j=1}^{J}\sum_{m=1}^{M} {PW_{i,j}^{m}}^2 + \sum_{j=1}^{J} \sigma c' h_j \sum_{k=1}^{K}\sum_{n=1}^{N} {WC_{j,k}^{n}}^2 + \sum_{k=1}^{K} \sigma c' c_k \sum_{k=1}^{K}\sum_{n=1}^{N} {WC_{j,k}^{n}}^2 \\ &+ \sum_{l=1}^{L} \sigma c' d_l \sum_{k=1}^{K}\sum_{o=1}^{O} {CI_{k,l}^{0}}^2 + \sum_{i=1}^{I} \sigma c' r_i \sum_{l=1}^{L}\sum_{v=1}^{V} {IP_{l,i}^{v}}^2 + \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{m=1}^{M} \sigma c'' p_{i,j}^{m}\, {PW_{i,j}^{m}}^2 \\ &+ \sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{n=1}^{N} \sigma c'' w_{j,k}^{n}\, {WC_{j,k}^{n}}^2 + \sum_{k=1}^{K}\sum_{l=1}^{L}\sum_{o=1}^{O} \sigma c'' c_{k,l}^{o}\, {CI_{k,l}^{0}}^2 \\ &+ \sum_{l=1}^{L}\sum_{i=1}^{I}\sum_{v=1}^{V} \sigma c'' d_{l,i}^{v}\, {IP_{l,i}^{v}}^2 + \sum_{k=1}^{K} \sigma c' q_k\ {SH_k}^2 \end{aligned} \tag{5}$$

$$
\begin{aligned}
minZ_3 = &\sum_{i=1}^{I} rp_i \sum_{j=1}^{J}\sum_{m=1}^{M} PW_{i,j}^m + \sum_{j=1}^{J} rw_j \sum_{k=1}^{K}\sum_{n=1}^{N} WC_{j,k}^n + \sum_{l=1}^{L} rd_l \sum_{k=1}^{K}\sum_{o=1}^{O} CI_{k,l}^0 \\
&+ \sum_{i=1}^{I} rr_i \sum_{l=1}^{L}\sum_{v=1}^{V} IP_{l,i}^v + \sum_{m=1}^{M} r''p_m \sum_{i=1}^{I}\sum_{j=1}^{J} \alpha p_{i,j}^m\, sp_{i,j} PW_{i,j}^m \\
&+ \sum_{n=1}^{N} r''w_n \sum_{j=1}^{J}\sum_{k=1}^{K} \alpha w_{j,k}^n\, sw_{j,k} WC_{j,k}^n + \sum_{o=1}^{O} r''c_o \sum_{k=1}^{K}\sum_{l=1}^{L} \alpha c_{k,l}^o\, sc_{k,l} CI_{k,l}^0 \\
&+ \sum_{v=1}^{V} r''d_p \sum_{j=1}^{J}\sum_{k=1}^{K} \alpha d_{l,i}^v\, sd_{l,i} IP_{l,i}^v
\end{aligned} \tag{6}
$$

The objective functions Z_1 and Z_2 minimize the mean and variance of the random variable $\tilde{Y}$. Z_3 represents the carbon dioxide gas released through production, reproduction, storage, disassembly, collection, and transportation between components.

$$\sum_{j=1}^{J}\sum_{m=1}^{M} PW_{i,j}^m \le up_i Fp_i \qquad \forall i \in I \tag{7}$$

$$\sum_{l=1}^{L}\sum_{v=1}^{V} IP_{l,i}^v \le ur_i Fp_i \qquad \forall i \in I \tag{8}$$

$$\sum_{i=1}^{I}\sum_{m=1}^{M} PW_{i,j}^m \le uw_j Fw_j \qquad \forall j \in J \tag{9}$$

$$\sum_{k=1}^{K}\sum_{o=1}^{O} CI_{k,l}^0 \le ud_l Fd_l \qquad \forall\, l \in L \tag{10}$$

Eqs 7 and 8 represent that each factory operates according to its production and reproduction capacity. Eqs 9 and 10 also demonstrate the warehouses' storage capacity and the disassembly capacity in the DCs.

$$\sum_{i=1}^{I}\sum_{m=1}^{M} PW_{i,j}^m \ge \sum_{k=1}^{K}\sum_{n=1}^{N} WC_{j,k}^n \qquad \forall j \in J \tag{11}$$

Eq. 11 shows that each warehouse's output flow must be less than or equal to the input flow. This constraint is used for material flow balances.

$$\sum_{j=1}^{J}\sum_{n=1}^{N} WC_{j,k}^n + SH_k \ge d_k \qquad \forall k \in K \tag{12}$$

Eq. 12 indicates that the demand of each customer may face a shortage. In case the customer is not exposed to the shortage, different warehouses should meet the demand.

$$\sum_{l=1}^{L}\sum_{o=1}^{O} CI_{k,l}^{0} + SH_k \leq d_k \qquad \forall k \in K \tag{13}$$

Each customer can return the disposal as much as the total amount of products received, shown in Eq. 13.

$$\sum_{l=1}^{I}\sum_{o=1}^{O} CI_{k,l}^{0} + \mu\gamma SH_k + Z_{1-\beta}\sqrt{\sigma\gamma {SH_k}^2 + \sigma\gamma {d_k}^2} \geq \mu\gamma d_k \qquad \forall k \in K \tag{14}$$

$$\sum_{i=1}^{I}\sum_{v=1}^{V} IP_{l,i}^{v} + Z_{1-\beta}\sqrt{\sigma\gamma' \sum_{k=1}^{K}\sum_{o=1}^{O} {CI_{k,l}^{0}}^{2}} \geq \mu\gamma' \sum_{k=1}^{K}\sum_{o=1}^{O} CI_{k,l}^{0} \qquad \forall l \in L \tag{15}$$

The deterministic form of random constraints presented in Eqs 2 and 3 is shown by nonlinear inequalities in formulas 14 and 15. These constraints force the model to establish a reverse flow in the SC.

$$Fp_i\ , Fw_j\ , Fd_l \in \{0,1\} \tag{16}$$

$$PW_{i,j}^{m} \geq 0,\ WC_{j,k}^{n} \geq 0,\ CI_{k,l}^{0} \geq 0,\ IP_{l,i}^{v} \geq 0,\ SH_k \geq 0 \tag{17}$$

Eq. 16 represents the binary variables related to strategic decisions, and Eq. 17 shows the continuous decision variables related to the tactical decisions.

IV. METHODOLOGY

A novel multi-objective model was solved by using the Goal-attainment (GA) method. GA is an extended form of the goal-programming provided by Gembicki (1974). This method's unique feature is the lower number of modeling variables, leading to faster computational performance. In the GA method, the maximum diversion of objectives from their goals is minimized using the following developed model:

$$\begin{aligned} &\min y \\ &s.t: \\ &w_j y \geq Q_j - Q_j^* \\ &y\ is\ un-restricted\ in\ sign \\ &Q_j \in S \end{aligned} \tag{18}$$

Q_j demonstrates the value of the j^th objective function and Q_j^* represents the optimal value of the j^th objective obtained by individual optimization, which is considered as the goal. Also, w_j represents the weight of the j_th objective, which is inversely related to the priority of the objectives.

V. APPLICATION:A NUMERICAL EXAMPLE

Ten problem tests with different sizes were considered and coded to evaluate the proposed model's performance and the GA method, using the GAMS 25.1.2 software on a Core i7 personal computer with an 8.00 GB RAM. As expected, CPU time was raised dramatically as the problem size was increased.

Table VI. The values of the objective functions and CPU time after solving problem tests

Number	*Problem Test Size* $(i \times j \times k \times l \times m \times n \times o \times p)$	*Expected Value of Cost* (*million Rials*)	*Variance of Cost* $(million\ Rials)^2$	*Total* co_2 *emissions* (kg)	*CPU Time* (*second*)
1	2*2*5*2*2*2*2*2	22777.512	264084.316	155902.963	0.590
2	3*3*8*3*2*2*2*2	41266.510	515086.118	327132.971	7.760
3	3*3*8*3*3*3*3*3	23637.074	236370.073	166370.736	8.85
4	5*5*10*5*3*3*3*3	40937.499	317462.038	209280.685	4.310
5	7*10*15*7*3*3*3*3	60921.573	404748.706	296567.353	25.790
6	8*12*17*8*2*2*2*2	66916.035	464029.180	355847.827	18.310
7	10*15*25*10*3*3*3*3	111396.825	667270.638	559089.285	216.040
8	15*20*30*15*2*2*2*2	133945.136	773983.485	665802.132	190.340
9	20*30*50*20*1*1*1*1	210424.368	1205639.093	1097457.740	305.930
10	25*40*80*25*1*1*1*1	347094.418	1978445.376	1870264.023	992.030

Among the offered problem tests, problem 3 with 3 factories, 3 warehouses, 8 customers, 3 DCs, and 3 transportation methods, among facilities, could be considered as a primary problem for further analysis. Table 7 presents the values of uncertain parameters and deterministic customer demands of the main problem. All non-deterministic parameters of the problem were modeled using the normal distribution with specified mean and variance.

According to Table VIII, the goals of Z_1, Z_2 and Z_3 are 23495.936 million Rials, 34439.913 (million Rials)^2 and 0 kg, respectively. After solving the main problem using the GA method, the values of continuous decision variables are illustrated in Table IX. Figure 2 also demonstrates a graphical view of the designed green closed-loop supply chain and selected transportation modes in which plant 3, warehouses 1 and 2, and DC 2 have been built.

For sensitivity analysis, different priorities for each of the objectives were considered. Table 10 shows that the reduction of the weight of each objective increases their priority in making decisions. Also, the process of the interaction of goals with each other based on the values of w_j is shown in Figures 3, 4, 5.

Table VII. Values of the uncertain parameters

Parameter	*Value*	*Parameter*	*Value*	*Parameter*	*Value*	*Parameter*	*alue*
cp_1	$N(120, 169)$	$c'h_3$	$N(52, 25)$	$c'q_2$	$N(165, 81)$	d_1	18
cp_2	$N(143, 121)$	$c'c_1$	$N(20, 9)$	$c'q_3$	$N(192, 100)$	d_2	26
cp_3	$N(132, 144)$	$c'c_2$	$N(30, 16)$	$c'q_4$	$N(180, 121)$	d_3	15
cw_1	$N(112, 121)$	$c'c_3$	$N(32, 25)$	$c'q_5$	$N(162, 169)$	d_4	21
cw_2	$N(140, 144)$	$c'c_4$	$N(26, 25)$	$c'q_6$	$N(190, 49)$	d_5	16
cw_3	$N(112, 100)$	$c'c_5$	$N(25, 31)$	$c'q_7$	$N(190, 225)$	d_6	20
cd_1	$N(70, 49)$	$c'c_6$	$N(25, 37)$	$c'q_8$	$N(161, 49)$	d_7	18
cd_2	$N(75, 36)$	$c'c_7$	$N(30, 40)$	$c'r_1$	$N(25, 9)$	d_8	17
cd_3	$N(72, 36)$	$c'c_8$	$N(28, 64)$	$c'r_2$	$N(27, 16)$	$Z_{1-\beta}$	1.645
$c'p_1$	$N(68, 25)$	$c'c_8$	$N(27, 9)$	$c'r_3$	$N(30, 26)$	γ	$N(120, 169)$
$c'p_2$	$N(58, 36)$	$c'd_1$	$N(19, 9)$	$c''p_{i,j}^{m}$	$N(\mu, \sigma^2)$ $12 \leq \mu \leq 32$ $1 \leq \sigma^2 \leq 16$	γ'	$N(28, 64)$
$c'p_3$	$N(54, 25)$	$c'd_2$	$N(23, 9)$	$c''w_{j,k}^{n}$	$N(\mu, \sigma^2)$ $18 \leq \mu \leq 50$ $4 \leq \sigma^2 \leq 25$	β	0.05
$c'h_1$	$N(35,16)$	$c'd_3$	$N(20, 16)$	$c''c_{k,l}^{o}$	$N(\mu, \sigma^2)$ $19 \leq \mu \leq 50$ $4 \leq \sigma^2 \leq 25$		
$c'h_2$	$N(34, 16)$	$c'q_1$	$N(160, 100)$	$c''p_{l,i}^{v}$	$N(\mu, \sigma^2)$ $20 \leq \mu \leq 39$ $4 \leq \sigma^2 \leq 16$		

Table VIII. The value of the objective functions obtained by individual optimization

objectives	Z_1	Z_2	Z_3
MinZ_1	23495.936	300781.578	251427.469
MinZ_2	27696.084	34439.913	237343.743
MinZ_3	26379	312942	0

Table IX. The value of the continuous decision variables obtained by the goal attainment method

Decision variable	*Value*	*Decision variable*	*Value*	*Decision variable*	*Value*
$PW_{3,1}^{1}$	45.036	$WC_{2,5}^{1}$	4.330	$CI_{7,2}^{1}$	4.219
$PW_{3,1}^{2}$	7.472	$WC_{2,6}^{3}$	19.004	$IP_{2,3}^{2}$	7.311
$PW_{3,2}^{2}$	50.807	$WC_{2,7}^{2}$	18	SH_1	13.128
$WC_{1,2}^{3}$	15.513	$WC_{2,8}^{2}$	4.601	SH_2	10.487
$WC_{1,3}^{1}$	15	$CI_{2,2}^{1}$	2.815	SH_5	11.67
$WC_{1,4}^{2}$	21	$CI_{3,2}^{1}$	3.516	SH_8	12.399
$WC_{1,6}^{1}$	0.996	$CI_{4,2}^{3}$	4.922		
$WC_{2,1}^{3}$	4.872	$CI_{6,2}^{2}$	4.688		

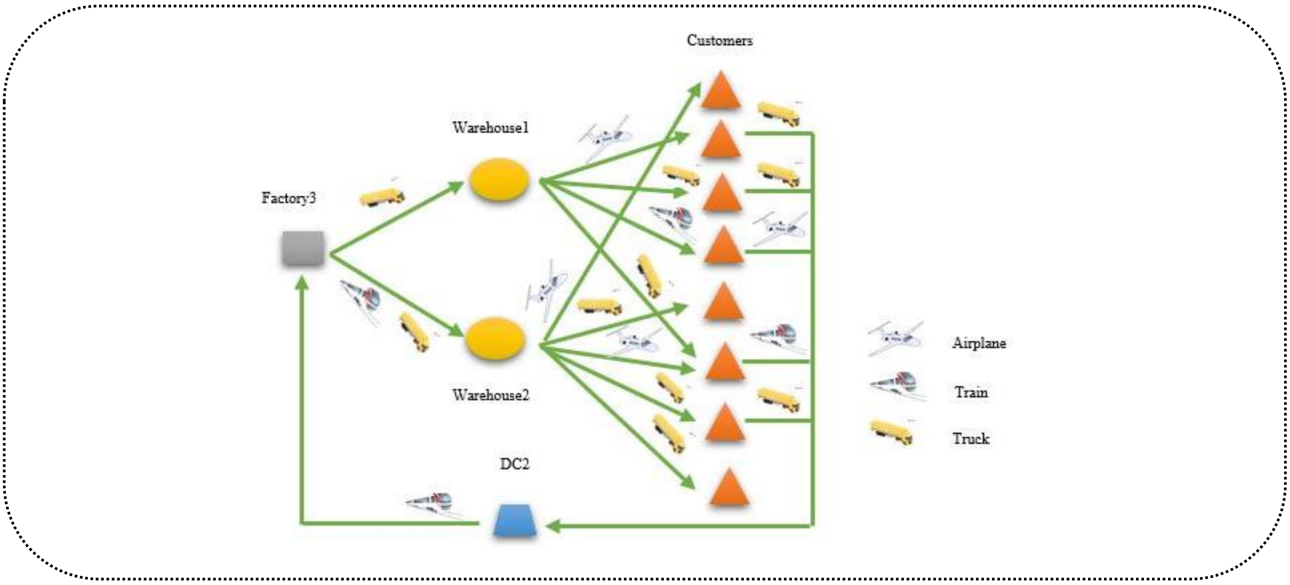

Fig. 2. The structure of the designed green supply chain network along with selected transportation modes among facilities

Table X. Results of the goal attainment method with different priorities for each of the objectives

Number of examples	w_1	w_2	w_3	Z_1 *(million rials)*	Z_2 *(million rials)*^{2}	Z_3 *(kg)*	*CPU time (s)*
1	0.1	0.1	0.8	23495.94	227945	256304.5	10.84
2	0.15	0.15	0.7	23507.14	235071.4	220333.3	5.34
3	0.20	0.20	0.6	23541.08	235410.8	196232.4	4.79
4	0.25	0.25	0.5	23587.91	235879.1	181758.3	6.4
5	0.3	0.3	0.4	23621.02	236210.1	171613.5	4.18
6	0.33	0.33	0.33	23637.07	236370.7	166370.7	4.7
7	0.35	0.35	0.3	23643.79	236437.8	164089.6	4.5
8	0.4	0.4	0.2	23660.03	236600.3	158300.1	4.18
9	0.45	0.45	0.1	23672.11	236721.1	153715.8	4.1

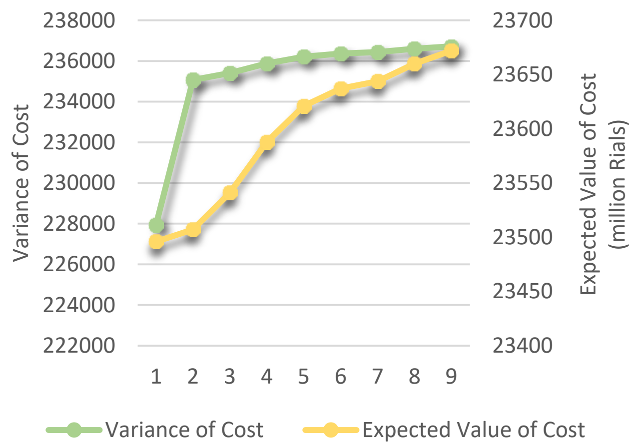

Fig. 3. Comparison between the trend of the expected value and the variance of cost

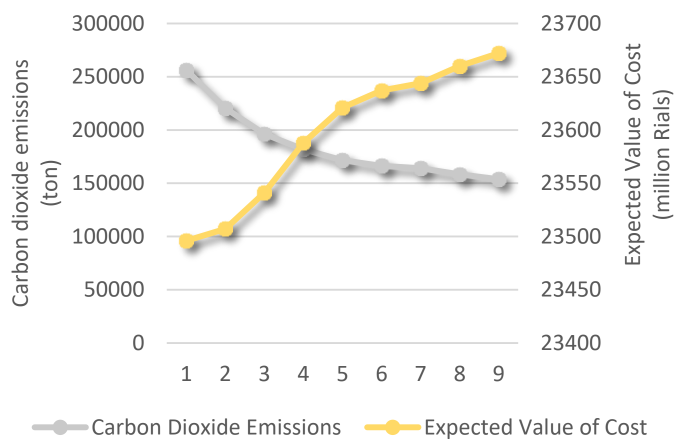

Fig. 4. Comparison between the trend of the expected value of cost and the total co_2 released

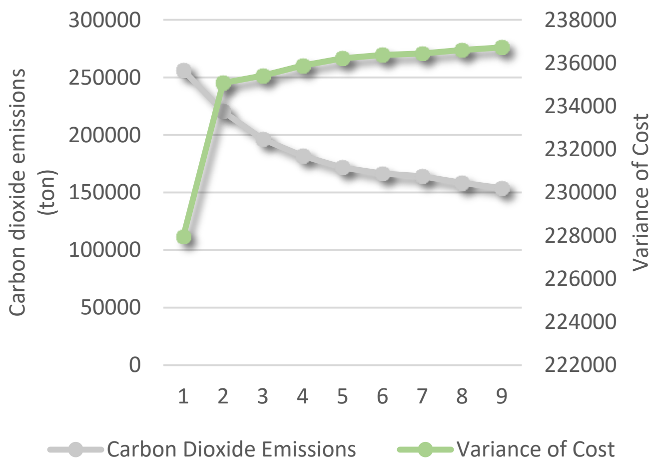

Fig. 5. Comparison between the trend of cost variance and the total co_2 released

One of the most fundamental parameters affecting the objective functions is the uncertain parameters. Figures 6 and 7 demonstrate the effect of raising the mean of $\tilde{\gamma}$ and $\tilde{\gamma}'$on the value of Z_1, Z_2 and Z_3 functions. Based on the shown trends, the value of the objective functions grows with increasing the value of $\mu\gamma$ and $\mu\gamma'$. Changing the mean of the minimum percentage of the units of product to be disposed and collected from a customer has a more significant impact on the objective functions than changing the mean of the minimum percentage of the product units to be dismantled to be shipped from a DC.

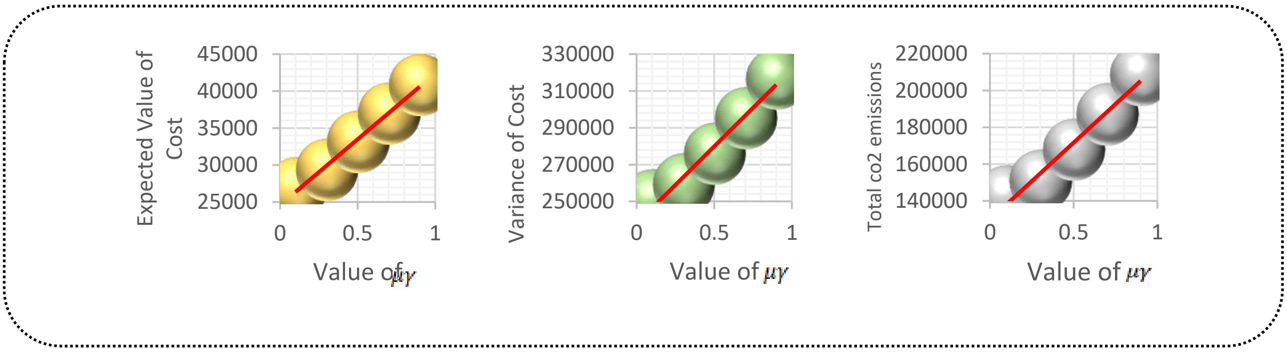

Fig. 6. The impact of raising the value of $\mu\gamma$ on the objective functions

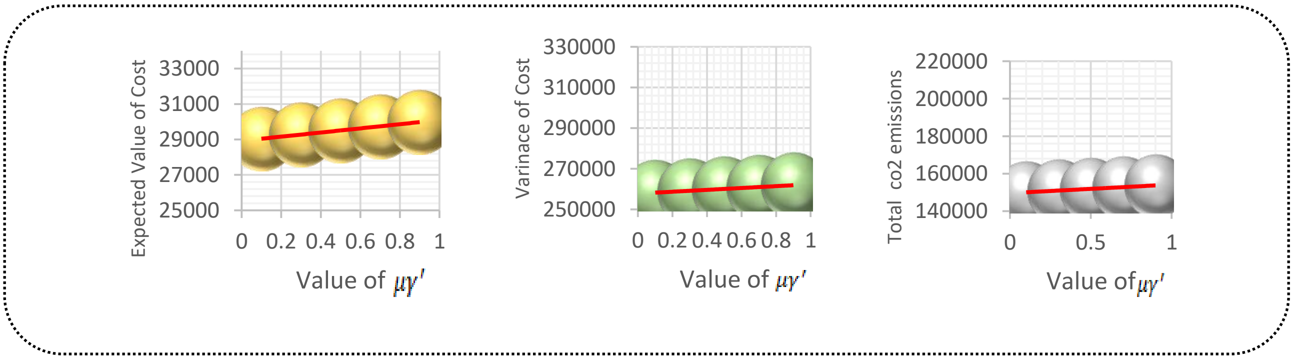

Fig. 7. The impact of raising the value of $\mu\gamma'$on the objective functions

Figures 8, 9, and 10 illustrate the effect of raising the chance constraints confidence level on the objective functions' values. As expected, with increasing $1-\beta$, the expected value and variance of the cost and total carbon dioxide emissions would be reduced. For the function of the cost expected value, this reduction could reach 6264,218 million Rials.

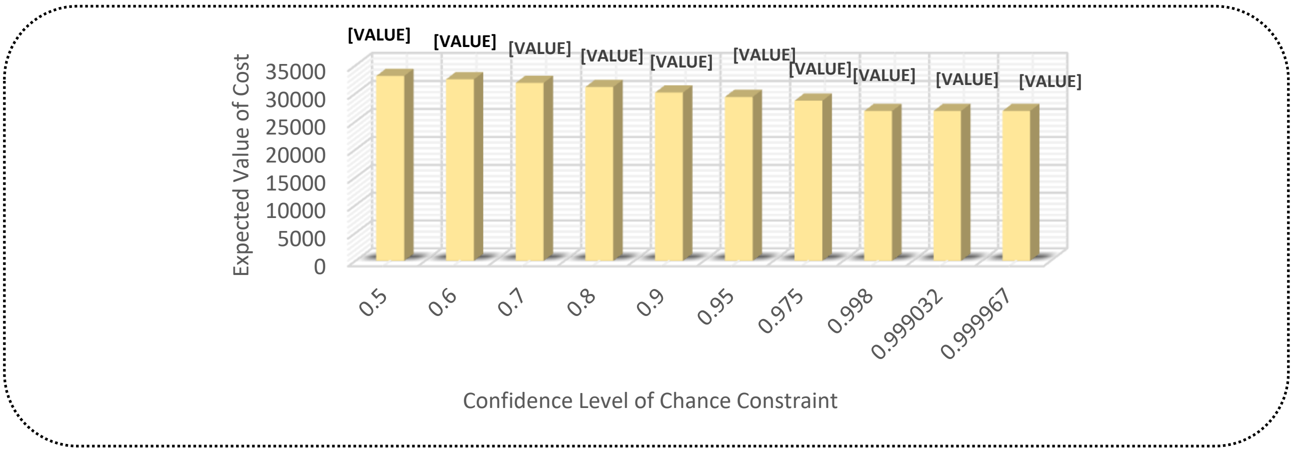

Fig. 8. Graphical representation of the expected value of cost under different confidence levels

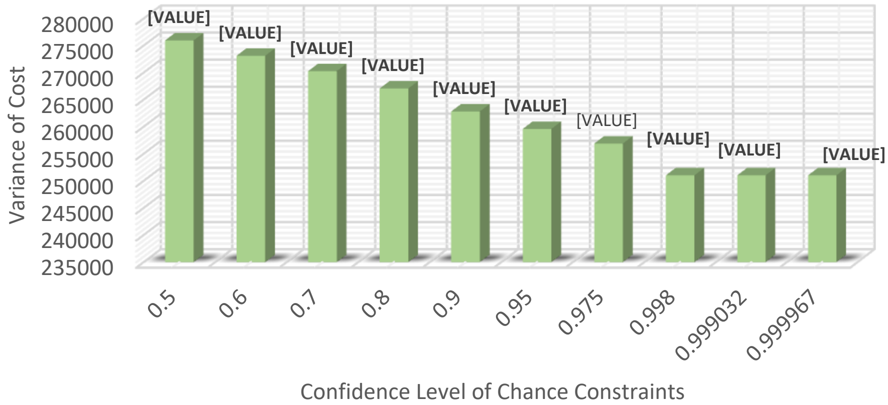

Fig. 9. Graphical representation of the value of cost variance under different confidence levels

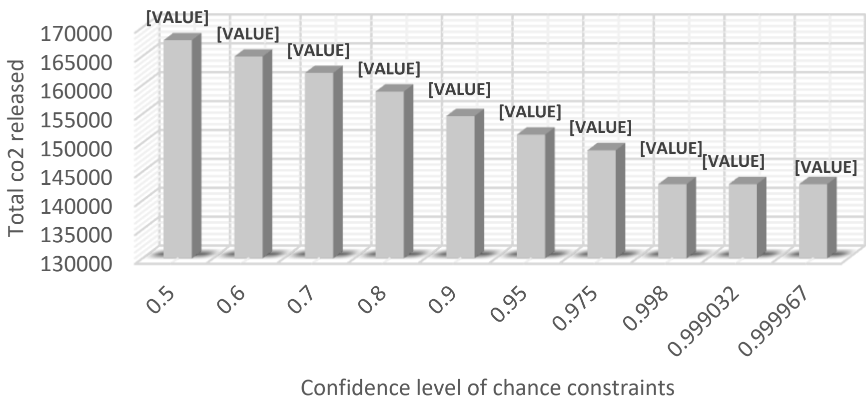

Fig. 10. Graphical representation of the value of the total carbon dioxide emission under different confidence levels

VI. CONCLUSION AND SUGGESTIONS FOR FUTURE WORKs

Designing effective networks is one of the most critical issues in supply chain management. Considering the environmental requirements and controlling the uncertainties in the networks' design process have led to the development of the concept of sustainability in the supply chains. In this study, a novel three-objective programming model was developed by taking into account the useful random parameters for locating facilities and flowing between them in a green closed-loop supply chain consisting of factories, warehouses, customers, and DCs. The objectives were to minimize the total expected value and variance of costs and minimize carbon dioxide emissions. The most critical assumptions of the problem are the allowable shortage, the uncertainty of some new parameters, and the different transportation modes between facilities. The model was solved using the GA method, and the efficiency of the model was evaluated by providing model sensitivity analysis on the sensitive parameters. Accordingly, by reducing the parameters related to establishing the return flow and increasing the confidence level of random constraints, the objective functions were improved.

The model presented in this study has a good potential for improvement by adding new hypotheses and solving through heuristic and meta-heuristic methods. Future research suggestions are presented in the following four categories: adding new assumptions, new modeling methods, efficient methods for modeling uncertainties, and expanding the solution methods.

I. Developing a mathematical model in multi-product and multi-period mode,
II. Adding capacity for each transportation mode,
III. Improving the social dimension of sustainability,
IV. Adding new objective functions, such as minimizing risk and waste, maximizing agility, etc.
V. Developing large-scale solving methods using heuristic and meta-heuristic algorithms, as well as exact algorithms.
VI. Using other multi-objective decision-making methods such as goal programming, global criteria, Epsilon constraint, etc.

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