A ROBUST MULTI-OBJECTIVE MODEL FOR MANAGING THE DISTRIBUTION OF PERISHABLE PRODUCTS WITHIN A GREEN CLOSED-LOOP SUPPLY CHAIN

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ABSTRACT. The required processes of supply chain management include optimal strategic, tactical, and operational decisions, all of which have important economic and environmental effects. In this regard, efficient supply chain planning for the production and distribution of perishable products is of particular importance due to its leading role in the human food pyramid. One of the main challenges facing this chain is the time when products and goods are delivered to the customers and customer satisfaction will increase through this. In this research, a bi-objective mixed-integer linear programming (MILP) model is proposed to design a multi-level, multi-period, multi-product closed-loop supply chain (CLSC) for timely production and distribution of perishable products, taking into account the uncertainty of demand. To face the model uncertainty, the robust optimization (RO) method is utilized. Moreover, to solve and validate the bi-objective model in small-size problems, the \( \varepsilon \)-constraint method (EC) is presented. On the other hand, a Non-dominated Sorting Genetic Algorithm (NSGA-II) is developed for solving large-size problems. First, the deterministic and robust models are compared by applying the suggested solutions methods in a small-size problem, and then, the proposed solution methods are compared in large-size problems in terms of different well-known metrics. According to the comparison, the proposed model has an acceptable performance in providing the optimal solutions and the proposed algorithm obtains efficient solutions. Finally, managerial insights are proposed using sensitivity analysis of important parameters of the problem.

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1. Introduction. Supply chain design, and its related transportation and logistics systems is an important issue for all segments of society due to its effects on the main variables of the country’s economy such as production, employment, price, and cost of living index [61]. In the past, each production center tried to increase its market share by paying attention to the number of products produced, but in today’s competitive circumstances, it is clear that production centers and companies seek to create strategic and operational decisions to optimize and manage their logistic systems. Therefore, to gain more advantage in the market, they should look for solutions by which they can reduce costs and increase customer satisfaction continuously and simultaneously. Customer satisfaction increases if products and goods reach customers within a certain time. Especially in the fields of perishable products, research has shown that shipping costs are a great part of the cost of the products.

One of the vital operational decisions related to these challenges is the use of a multi-level system for the distribution of goods, which causes a large reduction in costs and improves service quality. In addition to the economic aspects, the use of this type of distribution system leads to reduced traffic, environmental pollution, and noises in the city centers, because the vehicles of the last level are smaller and provide more satisfaction to the citizens [2].

Perishable products are the items that may be damaged or spoiled over time by changes in temperature, pressure, humidity, or any environmental conditions, such as food, dairy, vegetables, meat, medicine, etc. The perishable supply chain has always been one of the most significant and attractive issues in supply chain management at different times. The challenge for companies in managing perishable food supply chains is that the value of the product is highly dependent on the environment over time. Shipping time, temperature, pressure, and humidity are the key elements in transporting perishable items. Carrying such materials, it is necessary to observe the requirements in which the mentioned variables can be controlled. Any changes in the mentioned elements can affect the quality of the shipped products.

Failure to comply with the required standards at any point in the supply chain of perishable products, can cause irreparable damage to the customer’s products and make them unusable. Therefore, choosing the shipping method is highly important. So, the distribution of perishable products throughout the supply chain with the highest possible quality is one of the most significant competitive processes in the field of perishable products and companies should give heed to this concept while designing the optimal supply chain.

In this research, it is intended to design a mathematical model for a green CLSC network for perishable products and with uncertain demand, which tries to minimize costs and environmental pollution simultaneously. To cope with the uncertainty of the parameters, a Robust Optimization (RO) approach is used and the efficiency of the model is evaluated according to the robust feasible solutions. To validate the proposed model, the bi-objective model is first transformed into a single-objective model by the $\epsilon$-constraint approach and then, is solved by designing numerical instances in the CPLEX solver. Additionally, a Non-dominated Sorting Genetic Algorithm (NSGA-II) is then designed to solve the large-size problems which are closer to real-world issues. Finally, results are presented to assess the efficiency of the algorithm and provide managerial insights at the chain level.

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. The robust model of the proposed problem is devolved in Section 4. Section 5 includes the design of solution methods. The validation of the suggested model and the computational results of the research are presented in Section 6 and finally, in Section 7, the conclusions and future suggestions are described.

2. Survey on the literature. In this section, the limited studies that have been conducted in the field of the perishable supply chain are reviewed as well as literature related to forward, reverse, and CLSCs under uncertainty.

Ozceylan et al. [37] modeled an integrated CLSC network and optimized the disassembly line balance. This paper considered strategic and tactical decisions simultaneously within a CLSC network. The objective was to minimize costs, including transportation, purchase, renovation, and dismantling station operations. Amin and Zhang [3] provided a multi-objective mathematical model including several commodities, factories, recycling technologies, demand markets, and collection centers. This model aimed at minimizing the costs of the supply chain, in addition to minimizing the waste rate and operation time in collection centers. Soleimani and Kannan [49] designed a large-scale multi-period, multi-level, multi-product CLSC network. They combined genetics and particle swarm optimization algorithms to improve the efficacy of the Genetic Algorithm (GA) by considering the positive aspects of Particle Swarm Optimization (PSO) algorithm.

Rezapour et al. [46] proposed a competitive CLSC network in the price-dependent demand market. They developed a two-level model that reverses strategic network decisions are made at a higher level and CLSC tactical and operational planning is done at the lower level. There is a competition between two supply chains to supply new products to similar markets and between a new supply chain to supply a new or remanufactured product. Li and Jia [33] presented a coordinated supply chain model considering product quality and stochastic demand. Zahiri and Pishvae [60] designed a blood supply chain network considering uncertainty. To this end, a bi-objective mixed-integer linear programming (MILP) model was suggested which aims to the minimization of cost and the maximization of demand fulfillment. Due to the uncertain nature of the data, two probabilistic robust models were developed based on the credibility criterion. The results of the case study indicated the appropriate efficiency of the offered models. Keshavarz et al. [26] developed a multi-objective multi-product multi-period reverse supply chain model considering uncertainty. The objectives were to minimize the total cost and maximize the green points of the purchased raw materials. In this regard, multi-objective decision-making methods were employed.

Heydari et al. [24] studied a coordinated supply chain model with random stochastic and considering the change in reordering time. Pal and Mahapatra [38] presented a production-based supply chain model considering inspection errors and incomplete quality of products in conditions of shortage and stochastic demand. Haddad Sisakht and Rayan [23] developed a CLSC network by considering different modes of transportation under stochastic demand and uncertain carbon tax rates. Their goal was to minimize the total cost of the supply chain at three levels. Kavyanfar et al. [25] developed a stochastic multi-product multi-level mathematical model to design the supply chain of small and medium industries in the clustering industry. Their suggested model aimed to minimize the total cost, which was solved by benders decomposition. They also presented a case study and sensitivity analysis to evaluate its efficiency. Dai et al. [14] developed a nonlinear model with fuzzy constraints to solve the location-routing problem (LRP) using GA and harmonic
search in a three-level supply chain network of perishable products. Their objective was to minimize the total costs of the supply chain. They employed LINDO software to evaluate their proposed algorithms and it was found that the proposed algorithms have a high ability to solve problems in a suitable operating time.

Tirkolaee et al. [50] developed a self-learning PSO algorithm to design a robust supply chain under uncertainty. They proposed an MILP model to deal with locational, allocation and inventory decisions. A novel MILP model was proposed by Goli et al. [19] to design a sustainable supply chain network for perishable products distribution. They considered lead times and customer satisfaction as two main criteria and implemented a hybrid meta-heuristic algorithm to tackle the complexity of the problem. Recently, Lotfi et al. [35] proposed an RO model to design a sustainable and resilient CLSC network. They addressed the conditional value at risk by developing a two-stage MILP model. Finally, the LP-Metric method and CPLEX solver were employed to find the optimal solution.

In Table 1, a summary of dominant and relevant research conducted in recent years is comprehensively reviewed.

| Reference                      | Year | Levels of Network | Features | Objectives | Solution methods |
|-------------------------------|------|-------------------|----------|------------|-----------------|
| Pishvaee et al.               | 2014 | * * * * * *       | *        | *          | LINGO           |
| Govindan et al.               | 2014 | * * * * *         |          |            | Benders         |
| Devika et al.                 | 2014 | * * * * * * *     |          |            | LINGO           |
| Ansieh et al.                 | 2015 | * * * *           |          |            | ϵ-constraint    |
| Wu et al.                     | 2017 | * * * * * *       |          | *          | NSGA-II         |
| Keshavarz Ghorabaee et al.    | 2017 | * * * * *         | *        | *          | GAMS            |
| Cheraghalipour et al.         | 2018 | * * * * *         |          | *          | NSGA-II         |
| Keyvanfar et al.              | 2018 | * * * * *         |          | *          | Benders         |
| Dai et al.                    | 2018 | * * * *           |          |            | LINGO           |
| Yousefi et al.                | 2019 | * * * * * * *     | *        | *          | Heuristics      |
| Parsa et al.                  | 2020 | * * * * * *       |          | *          | Branch-and-bound (B&B) algorithm |
| Lotfi et al.                  | 2021 | * * * * * * *     | *        | *          | LP-Metric method |
| Current work                  | 2021 | * * * * * * *     | *        | *          | ϵ-constraint and NSGA-II |
In this study, a novel MILP model is provided to configure a green CLSC for perishable products. Finally, after reviewing the literature, it is concluded that the research gap includes the following:

I. Designing a green CLSC network taking into account assumptions such as different production technology, different modes of transportation specific to perishable products that require special equipment and service at specific time windows. This is implemented by developing a bi-objective MILP model, including minimizing total costs and minimizing the total amount of emissions.

II. Making integrated optimal decisions for inventory management, location, and allocation of facilities and transportation planning.

III. Using the RO technique proposed by Bertsimas and Sim [8] to be applied to the developed model and comparing deterministic and uncertain conditions in different cases.

IV. Developing the \( \varepsilon \)-constraint method and NSGA-II to validate and solve the proposed model.

V. Implementing sensitivity analysis on the key parameters of the problem to investigate the behavior of objective functions and presenting managerial insights.

3. Problem description. In designing the supply chain of perishable products, customer satisfaction increases if products and goods reach customers within a certain period. Research has shown that a significant portion of the cost of products is related to shipping costs. In this regard, one of the vital operational decisions is the use of a multi-level system for the distribution of products, which leads to a large reduction in costs and improves service quality. In addition to the economic aspects, the use of this type of distribution system leads to a reduction in traffic, environmental pollution, and noise in city centers, because the final level vehicles are smaller and provides more satisfaction to the citizen.

In this problem, a seven-level CLSC network including supply centers, production centers, distribution centers, and customers in the forward supply chain and collection, disposal, and recovery centers in the reverse supply chain is considered. Figure 1 shows the proposed seven-level supply chain network.

Based on the proposed network, the problem aims to

- Determine the optimal locations of facilities at 5 levels of production, distribution, collection, disposal, and recovery,
- Calculate the quantity of products in production centers, the quantity of raw materials supplied from supply centers,
- Determine the level of inventory in distribution centers, The quantity of products sent from production centers to distribution, from distribution centers to customers, the quantity of products returned from customers to collection centers, and the quantity of products sent from collection centers to disposal and recovery centers,

As the main objective functions, the total cost of the supply chain network, and the total volume of pollutant emissions should be minimized.

On the other hand, the demand of customers is uncertain and defined in an uncertain interval.

Furthermore, at the production level, various production technologies along with various modes of transport between levels are considered. Also, an important feature of this supply chain is the timely supply and distribution of raw materials and
products due to their perishable nature. In the following, the main assumptions of the model are presented.

I. The proposed supply chain network includes seven levels: 1) supply centers 2) production centers 3) distributors 4) customers 5) collection centers 6) disposal centers and 7) recovery centers.

II. Determining the optimal location is done in 5 levels of manufacturer, distributor, collection, recovery, and disposal centers.

III. Customer demand is uncertain and takes value according to an uncertain interval which is specified by the RO approach.

IV. Several modes of transportation systems are considered in the supply chain network.

V. Several levels of production technology are considered.

VI. The capacity of various facilities and centers is limited.

VII. Costs of facility location, transportation, inventory shortage, and maintenance are fixed.

VIII. The problem is planned for one period.

IX. In each planning period, a certain time is considered for the delivery of raw materials from supply centers to production centers and delivery of products from distribution centers to customers.

X. Inventory shortage can occur in distribution centers.

XI. Several types of raw materials and several types of final products are considered.

XII. The volume of pollutant emissions depends on the amount of load and the distance traveled between different levels.
XIII. Each raw material is used in the production of the final product with a specific consumption coefficient.

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

**Sets and indices**

- \( s \) : Set of supply centers \((s \in S)\),
- \( p \) : Set of production centers \((p \in P)\),
- \( d \) : Set of distribution centers \((d \in D)\),
- \( c \) : Set of customers \((c \in C)\),
- \( m \) : Set of collection centers \((m \in M)\),
- \( q \) : Set of disposal centers \((q \in Q)\),
- \( o \) : Set of recovery centers \((o \in O)\),
- \( t \) : Set of time periods \((t \in T)\),
- \( r \) : Set of products \((r \in R)\),
- \( a \) : Set of raw materials supplied from suppliers \((a \in A)\),
- \( e \) : Set of transportation mode from supply centers to production centers \((e \in E)\),
- \( f \) : Set of transportation mode from production centers to distribution centers \((f \in F)\),
- \( g \) : Set of transportation mode from distribution centers to the customers \((g \in G)\),
- \( h \) : Set of transportation mode from customers to the collection centers, from collection centers to recovery and disposal center and from there to the production center \((h \in H)\),
- \( w \) : Set of production technology \((w \in W)\).

**Parameters**

- \( DE_{crt} \) : Demand of customer \( c \) for product \( r \) in period \( t \),
- \( DA_{art} \) : Quantity of raw material type \( a \) required to produce one unit of product \( r \) in period \( t \),
- \( RA_{ar} \) : Consumption coefficient of raw material type \( a \) to produce one unit of product \( r \),
- \( OA_{aro} \) : Recovery coefficient of product \( r \) to raw material type \( a \) in the recovery center \( o \),
- \( CAS_{sa} \) : Capacity of supply center \( s \) to supply raw material type \( a \) in each period,
- \( CAP_{prw} \) : Capacity of production center \( p \) for product \( r \) with technology \( w \) in each period,
- \( CAD_{dr} \) : Capacity of distribution center \( d \) for product \( r \) in each period,
- \( CAM_{mr} \) : Capacity of collection center \( m \) for product \( r \) in each period,
- \( CAQ_{qr} \) : Capacity of disposal center \( q \) for product \( r \) in each period,
- \( CAO_{or} \) : Capacity of recovery center \( o \) for product \( r \) in each period,
- \( ESP_{spate} \) : Cost of transporting raw material \( a \) from the supplier \( s \) to the producer \( p \) with transportation mode \( e \) in the period \( t \),
- \( GSP_{spae} \) : Volume of \( CO_2 \) emission (depends on the volume of load and the distance) for transport one unit of raw material \( a \) from the supplier \( s \) to the producer \( p \) with transportation mode \( e \),
- \( TSP_{spae} \) : Preparation and transportation time of raw material \( a \) from supplier \( s \) to producer \( p \) with transportation mode \( e \),
- \( EPD_{pdrtf} \) : Cost of transporting the product \( r \) from manufacturer \( p \) to distributor \( d \) with transportation mode \( f \) in period \( t \).
\( GPD_{pdrf} \): Cost of transporting product \( r \) from manufacturer \( p \) to distributor \( d \) with transportation mode \( f \) in period \( t \),

\( EDC_{dcrtg} \): Cost of transporting product \( r \) from distributor \( d \) to customer \( c \) with transportation mode \( g \) in period \( t \),

\( GDC_{dcrq} \): Volume of \( CO_2 \) emission (depends on the volume of load and the distance) for transport a unit of product \( r \) from distributor \( d \) to customer \( c \) with transportation mode \( g \),

\( TDC_{dcrq} \): Preparation and transportation time of product \( r \) from distributor \( d \) to customer \( c \) with transportation mode \( g \) in each period,

\( ECM_{cmrth} \): Cost of transporting the product \( r \) from customer \( c \) to collection center \( m \) with transportation mode \( h \) in period \( t \),

\( GCM_{cmrth} \): Volume of \( CO_2 \) emission (depends on the volume of load and the distance) for transport a unit of product \( r \) from customer \( c \) to collection center \( m \) with transportation mode \( h \),

\( EMQ_{mqrth} \): Cost of transporting the product \( r \) from collection center \( m \) to disposal center \( q \) with transportation mode \( h \) in period \( t \),

\( GMQ_{mqrh} \): Volume of \( CO_2 \) emission (depends on the volume of load and the distance) for transport a unit of product \( r \) from collection center \( m \) to disposal center \( q \) with transportation mode \( h \),

\( EMO_{morth} \): Cost of transporting the product \( r \) from collection center \( m \) to recovery center \( o \) with transportation mode \( h \) in period \( t \),

\( GMO_{morth} \): Volume of \( CO_2 \) emission (depends on the volume of load and the distance) for transport a unit of product \( r \) from collection center \( m \) to recovery center \( o \) with transportation mode \( h \),

\( EOP_{oprth} \): Cost of transporting the returned processed product \( r \) to recover in recovery center \( o \) and production center \( p \) with transportation mode \( h \) in period \( t \),

\( GOP_{oprth} \): Volume of \( CO_2 \) emission (depends on the volume of load and the distance) for transport a unit of returned processed product \( r \) to recover in recovery center \( o \) and production center \( p \) with transportation mode \( h \) in period \( t \),

\( U_Ee \): Capacity of transportation mode \( e \),

\( U_Ff \): Capacity of transportation mode \( f \),

\( U_Gg \): Capacity of transportation mode \( g \),

\( U_Hh \): Capacity of transportation mode \( h \),

\( DS_{sp} \): Distance between supply center \( s \) and producer \( p \),

\( DB_{pd} \): Distance between producer \( p \) and distributor \( d \),

\( DC_{dc} \): Distance between distributor \( d \) and customer \( c \),

\( DD_{cm} \): Distance between customer \( c \) and collection center \( m \),

\( DM_{mq} \): Distance between collection center \( m \) and disposal center \( q \),

\( DF_{mo} \): Distance between collection center \( m \) and recovery center \( o \),

\( DG_{op} \): Distance between recovery center \( o \) and producer \( p \),

\( \alpha_{rc} \): Flow rate of returned product type \( r \) from customer \( c \) in each period,

\( \beta_r \): Flow rate of disposable product type \( r \) which are transferable from collection centersto disposal centers,

\( 1 - \beta_r \): Flow rate of recoverable product type \( r \) which are transferable from collection centersto disposal centers,

\( CP_{prtw} \): Production cost of product type \( r \) in period \( t \) by manufacturer \( p \) with technology \( w \),

\( CD_{drt} \): Processing cost of product type \( r \) in distribution center \( d \) in period \( t \),

\( CM_{mrt} \): Processing cost of product type \( r \) in collection center \( m \) in period \( t \),
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$CQ_{qrt}$: Processing cost of product type $r$ in disposal center $q$ in period $t$,
$CO_{ort}$: Processing cost of product type $r$ in recovery center $o$ in period $t$,
$FP_{ptw}$: Fixed cost of establishing production center $p$ in period $t$ with production technology $w$,
$FD_{dt}$: Fixed cost of establishing distribution center $d$ in period $t$,
$FM_{mt}$: Fixed cost of establishing collection center $m$ in period $t$,
$FQ_{qt}$: Fixed cost of establishing disposal center $q$ in period $t$,
$FO_{ot}$: Fixed cost of establishing recovery center $o$ in period $t$,
$HD_{drt}$: Unit inventory cost of product $r$ in distribution center $d$ in period $t$,
$BD_{drt}$: Unit shortage cost of product $r$ in distribution center $d$ in period $t$,
$(LP_{at}, UP_{at})$: Time window for supplying raw materials type $a$ in period $t$ to manufacturers,
$(LC_{crt}, UC_{crt})$: Time window for delivering product $r$ in period $t$ to customer $c$,
$MM$: A very large number.

Variables

$XP_{ptw}$: Quantity of product $r$ produced by the producer $p$ in period $t$ by the production technology $w$,
$XA_{spate}$: Quantity of raw material type $a$ transported from supply center $s$ to production center $p$ in period $t$ with the transportation mode $e$,
$XB_{pdrtf}$: Quantity of product $r$ transported from production center $p$ to distribution center $d$ in period $t$ and with transportation mode $f$,
$XC_{dcrtg}$: Quantity of product $r$ transported from distribution center $d$ to customer $c$ in period $t$ and with transportation mode $g$,
$XD_{cmerth}$: Quantity of product $r$ returned from customer $c$ to collection center $m$ in period $t$ with transportation mode $h$,
$XE_{mghth}$: Quantity of product $r$ transported from collection center $m$ to disposal center $q$ in period $t$ and with transportation mode $h$,
$XF_{morth}$: Quantity of product $r$ transported from collection center $m$ to recovery center $o$ in period $t$ and with transportation mode $h$,
$XG_{oparh}$: Quantity of recovered raw material $a$ from product $r$ which is transported from recovery center $o$ to production center $p$ in period $t$ with transportation mode $h$,
$ZA_{spate}$: 1 if raw material type $a$ is transported from distribution center $d$ to customer $c$ in period $t$ with transportation mode $g$, otherwise 0.
$ZB_{dcrtg}$: 1 if product $r$ is transported from distribution center $d$ to customer $c$ in period $t$ with transportation mode $g$, otherwise 0.
$YA_{pwt}$: 1 if production center $p$ is established with production technology $w$ in period $t$, otherwise 0.
$YB_{dt}$: 1 if distribution center $p$ is established in period $t$, otherwise 0.
$YC_{mt}$: 1 if collection center $m$ is established in period $t$, otherwise 0.
$YD_{qt}$: 1 if disposal center $q$ is established in period $t$, otherwise 0.
$YE_{ot}$: 1 if recovery center $o$ is established in period $t$, otherwise 0.
$IN_{drt}$: Inventory of product $r$ in distribution center $d$ at the end of period $t$.
$BO_{drt}$: Shortage of product $r$ in distribution center $d$ at the end of period $t$. 
3.1. Deterministic mathematical model. Objective functions

Objective function (1) minimizes the total cost of the supply chain, which is developed based on the modeling of similar works such as Yavari and Geraeli (2019) and Diabat et al. (2019).

\[
\text{minimize} \quad Z_1 = \sum_{s \in S} \sum_{p \in P} \sum_{a \in A} \sum_{t \in T} \sum_{e \in E} DS_{sp} ESP_{spate} X_{spate} \\
+ \sum_{p \in P} \sum_{d \in D} \sum_{r \in R} \sum_{t \in T} \sum_{f \in F} DB_{pd} EPD_{pdrtf} X_{pdrf} \\
+ \sum_{d \in D} \sum_{c \in C} \sum_{r \in R} \sum_{t \in T} \sum_{g \in G} DC_{dc} EDC_{dcrg} X_{C_{dcrg}} \\
+ \sum_{m \in M} \sum_{h \in H} \sum_{c \in C} \sum_{r \in R} \sum_{t \in T} DD_{cm} ECM_{cmrth} XD_{cmrth} \\
+ \sum_{m \in M} \sum_{q \in Q} \sum_{r \in R} \sum_{t \in T} DE_{mq} EMQ_{mqrth} XF_{mqrth} \\
+ \sum_{m \in M} \sum_{o \in O} \sum_{t \in T} \sum_{r \in R} \sum_{h \in H} DF_{mo} EMO_{morth} XF_{morth} \\
+ \sum_{o \in O} \sum_{p \in P} \sum_{a \in A} \sum_{r \in R} \sum_{t \in T} DG_{op} EOP_{oprtth} XG_{oparth} \\
+ \sum_{w \in W} \sum_{p \in P} \sum_{t \in T} FP_{ptw} Y_{A_{ptw}} + \sum_{d \in D} \sum_{t \in T} FD_{dt} Y_{B_{dt}} \\
+ \sum_{m \in M} \sum_{t \in T} FM_{mt} Y_{C_{mt}} + \sum_{q \in Q} \sum_{t \in T} FQ_{qt} Y_{D_{qt}} \\
+ \sum_{o \in O} \sum_{t \in T} FO_{ot} Y_{E_{ot}} + \sum_{d \in D} \sum_{r \in R} \sum_{t \in T} HD_{drt} Y_{I_{drt}} \\
+ \sum_{d \in D} \sum_{r \in R} \sum_{t \in T} BD_{drt} Y_{O_{drt}} + \sum_{w \in W} \sum_{p \in P} \sum_{r \in R} \sum_{t \in T} CP_{prtw} Y_{P_{prtw}} \\
+ \sum_{p \in P} \sum_{d \in D} \sum_{r \in R} \sum_{t \in T} X_{drtf} + \sum_{c \in C} \sum_{r \in R} \sum_{m \in M} \sum_{t \in T} \sum_{h \in H} CM_{mrt} Y_{D_{cmrth}} \\
+ \sum_{h \in H} \sum_{q \in Q} \sum_{m \in M} \sum_{r \in R} \sum_{t \in T} CQ_{qrt} Y_{E_{mqrth}} + \sum_{h \in H} \sum_{o \in O} \sum_{m \in M} \sum_{r \in R} \sum_{t \in T} CM_{ort} Y_{X_{f_{morth}}}
\]

Objective function (1) consists of four parts. The first part covers transportation costs at each stage of the forward and reverse supply chain. The first part also includes seven terms: the total cost of transportation between suppliers and producers, producers and distributors, distributors and customers, customers and collection centers, collection and disposal centers, collection and recovery centers, and finally between recovery centers and producers. The second part of the objective function includes the location cost of all facilities at different levels in the supply chain. This part of the objective function consists of 5 terms: the total cost of locating manufacturers, distributors, collection centers, disposal centers, and recovery centers. In the third part, the inventory and shortage costs of the distribution centers are calculated, respectively. Finally, in the fourth part, production costs,
operating costs in distribution centers, collection, and disposal, and recovery centers are determined.

\[
\begin{align*}
\text{minimize } Z_2 &= \sum_{s \in S} \sum_{p \in P} \sum_{a \in A} \sum_{t \in T} \sum_{e \in E} DA_{sp} GSP_{space} X_{space} A_{space} \\
&+ \sum_{p \in P} \sum_{d \in D} \sum_{r \in R} \sum_{t \in T} \sum_{f \in F} DB_{pf} GPD_{pf} X_{pf} B_{pf} \\
&+ \sum_{d \in D} \sum_{c \in C} \sum_{r \in R} \sum_{t \in T} \sum_{h \in H} DC_{dc} GDC_{dc} X_{dc} C_{dc} \\
&+ \sum_{m \in M} \sum_{o \in O} \sum_{r \in R} \sum_{t \in T} \sum_{h \in H} DM_{mo} GMQ_{mo} X_{mo} Q_{mo} \\
&+ \sum_{t \in T} \sum_{p \in P} \sum_{a \in A} \sum_{o \in O} \sum_{r \in R} \sum_{h \in H} DG_{op} GOP_{op} X_{op} G_{op} \\
&+ \sum_{p \in P} \sum_{d \in D} \sum_{r \in R} \sum_{t \in T} \sum_{f \in F} DB_{pf} GPD_{pf} X_{pf} B_{pf} \\
&+ \sum_{d \in D} \sum_{c \in C} \sum_{r \in R} \sum_{t \in T} \sum_{h \in H} DC_{dc} GDC_{dc} X_{dc} C_{dc} \\
&+ \sum_{m \in M} \sum_{o \in O} \sum_{r \in R} \sum_{t \in T} \sum_{h \in H} DM_{mo} GMQ_{mo} X_{mo} Q_{mo} \\
&+ \sum_{t \in T} \sum_{p \in P} \sum_{a \in A} \sum_{o \in O} \sum_{r \in R} \sum_{h \in H} DG_{op} GOP_{op} X_{op} G_{op} \\
&+ \sum_{p \in P} \sum_{d \in D} \sum_{r \in R} \sum_{t \in T} \sum_{f \in F} DB_{pf} GPD_{pf} X_{pf} B_{pf} \\
&+ \sum_{d \in D} \sum_{c \in C} \sum_{r \in R} \sum_{t \in T} \sum_{h \in H} DC_{dc} GDC_{dc} X_{dc} C_{dc} \\
&+ \sum_{m \in M} \sum_{o \in O} \sum_{r \in R} \sum_{t \in T} \sum_{h \in H} DM_{mo} GMQ_{mo} X_{mo} Q_{mo} \\
&+ \sum_{t \in T} \sum_{p \in P} \sum_{a \in A} \sum_{o \in O} \sum_{r \in R} \sum_{h \in H} DG_{op} GOP_{op} X_{op} G_{op} \\
\end{align*}
\]

Objective function (2) represents the minimization of the total volume of emissions within different levels of the supply chain. This objective function includes 7 terms: the total volume of pollution emissions between supply centers and producers, producers and distribution centers, distribution centers and customers, customers and collection centers, collection centers and disposal centers, collection centers and recovery centers, and finally between recovery centers and producers.

**Constraints**

\[
XP_{prtw} \leq CAP_{prw} YA_{put} \quad \forall p \in P, w \in W, t \in T, r \in R,
\]

Constraint (3) indicates the capacity limitation of each production center according to the level of technology in each period.

\[
\sum_{w \in W} YA_{put} \leq 1 \quad \forall p \in P, t \in T,
\]

Constraint (4) indicates that to build a production center, a level of technology must be chosen for it.

\[
\sum_{p \in P} \sum_{e \in E} X_{space} \leq CAS_{sa} \quad \forall s \in S, a \in A, t \in T,
\]

Constraint (5) shows the capacity limitation of supply centers for supplying raw materials in each period.

\[
\sum_{p \in P} \sum_{f \in F} XB_{pf} \leq CAD_{dr} YB_{dr} \quad \forall d \in D, r \in R, t \in T,
\]

Constraint (6) indicates the capacity limitation of distribution centers for distributing the products to the customers.

\[
\sum_{c \in C} \sum_{h \in H} XD_{cmrth} \leq CAM_{mr} YC_{mt} \quad \forall m \in M, r \in R, t \in T,
\]
Constraint (7) represents the capacity limitation of collection centers to collect returned products from the customer.

\[
\sum_{m \in M} \sum_{h \in H} X_{E \text{mqrth}} \leq CAQ_{qr}Y_{Dq}t \quad \forall q \in Q, r \in R, t \in T,
\]  

(8)

Constraint (8) indicates the capacity limitation of disposal centers for processing and disposal of products sent from collection centers.

\[
\sum_{m \in M} \sum_{h \in H} X_{F \text{morth}} \leq CAO_{or}Y_{Eot} \quad \forall o \in O, r \in R, t \in T,
\]  

(9)

Constraint (9) indicates the capacity limitation of recovery centers to process and recover products sent from collection centers.

\[
\sum_{s \in S} \sum_{p \in P} \sum_{e \in E} X_{A \text{spate}} + \sum_{o \in O} \sum_{p \in P} \sum_{h \in H} X_{C \text{oparth}} \geq DA_{art} \quad \forall a \in A, r \in R, t \in T,
\]  

(10)

Constraint (10) guarantees the balance of inventories in distribution centers in each time period.

\[
\sum_{d \in D} \sum_{g \in G} X_{D \text{cmrth}} = \alpha_{rc}\left(\sum_{d \in D} \sum_{g \in G} X_{C \text{dertg}}\right) \quad \forall r \in R, c \in C, t \in T,
\]  

(11)

Constraint (11) indicates the minimum volume of raw materials required to produce the final products in each period.

\[
\sum_{p \in P} \sum_{f \in F} XB_{pdrtf} = \sum_{c \in C} \sum_{g \in G} XC_{dertg} \quad \forall d \in D, r \in R, t \in T,
\]  

(12)

Constraint (12) shows the balance of the volume of input materials to production centers, which should be equal to the volume of final products sent from that production center to distribution centers in each period and according to the coefficient of consumption of raw materials.

\[
\sum_{m \in M} \sum_{h \in H} X_{E \text{mqrth}} = \beta_{r}(\sum_{m \in M} \sum_{h \in H} XD_{cmrth}) \quad \forall r \in R, t \in T,
\]  

(13)

Constraint (13) shows the balance of the volume of input materials to distribution centers, which should be equal to the volume of final products sent from that distribution center to the customers in each period.

\[
\sum_{m \in M} \sum_{h \in H} XD_{cmrth} = \alpha_{rc}\left(\sum_{d \in D} \sum_{g \in G} X_{C \text{dertg}}\right) \quad \forall r \in R, c \in C, t \in T,
\]  

(14)

Constraint (14) indicates the balance of the volume of input materials to collection centers, which should be equal to the volume of returned products (percentage of products received by the customer) by customers in each period.

\[
\sum_{q \in Q} \sum_{m \in M} \sum_{h \in H} X_{E \text{mqrth}} = \beta_{r}\left(\sum_{c \in C} \sum_{m \in M} \sum_{h \in H} XD_{cmrth}\right) \quad \forall r \in R, t \in T,
\]  

(15)

Constraint (15) indicates the balance of the volume of input materials to disposal centers, which should be equal to the volume of sent products (percentage of the
products of the collection center) by collection centers in each period.

\[
\sum_{o \in O} \sum_{m \in M} \sum_{h \in H} X F_{morth} = (1 - \beta_r) \left( \sum_{c \in C} \sum_{m \in M} \sum_{h \in H} X D_{cmrth} \right) \quad \forall r \in R, t \in T, \tag{16}
\]

Constraint (16) indicates the balance of the volume of input materials to recovery centers, which should be equal to the volume of sent products (percentage of the products of the collection center) by collection centers in each period.

\[
\sum_{p \in P} \sum_{h \in H} X G_{oparth} = OA_{aro} \left( \sum_{m \in M} \sum_{h \in H} X F_{morth} \right) \quad \forall a \in A, r \in R, o \in O, t \in T, \tag{17}
\]

Constraint (17) indicates the balance of the volume of input materials to recovery centers, which should be equal to the certain volume of recovered products (percentage of the products of the recovery center) by recovery centers in each period.

\[
\sum_{s \in S} \sum_{p \in P} \sum_{a \in A} X A_{spate} \leq U E_e \quad \forall e \in E, t \in T, \tag{18}
\]

Constraint (18) expresses the capacity limitation of transportation mode \( e \) in each time period.

\[
\sum_{d \in D} \sum_{p \in P} \sum_{r \in R} X B_{pdrtf} \leq U F_f \quad \forall f \in F, t \in T, \tag{19}
\]

Constraint (19) expresses the capacity limitation of transportation mode \( f \) in each time period.

\[
\sum_{d \in D} \sum_{c \in C} \sum_{r \in R} X C_{dcrtg} \leq U G_g \quad \forall g \in G, t \in T, \tag{20}
\]

Constraint (20) expresses the capacity limitation of transportation mode \( g \) in each time period.

\[
\sum_{r \in R} \sum_{m \in M} \sum_{c \in C} X D_{cmrth} + \sum_{r \in R} \sum_{m \in M} \sum_{q \in Q} X E_{mqrth} + \sum_{o \in O} \sum_{m \in M} \sum_{r \in R} X F_{morth} + \sum_{p \in P} \sum_{a \in A} \sum_{o \in O} \sum_{r \in R} X G_{oparth} \leq U_h \quad \forall h \in H, t \in T, \tag{21}
\]

Constraint (21) expresses the capacity limitation of the transportation mode \( h \) in each time period.

\[
X A_{spate} \leq MM(Z A_{spate}) \quad \forall s \in S, p \in P, a \in A, t \in T, e \in E, \tag{22}
\]

Constraint (22) determines the relationship between the allocations of production centers to supply centers with the volume of sent raw materials in each period.

\[
X C_{dcrtg} \leq MM(Z B_{dcrtg}) \quad \forall d \in D, c \in C, r \in R, t \in T, g \in G, \tag{23}
\]

Constraint (23) determines the relationship between the allocations of customers to distribution centers with the volume of sent products in each period.

\[
LP_{at} \left( \sum_{w \in W} Y A_{put} \right) \leq \sum_{s \in S} \sum_{e \in E} T S P_{spae} Z A_{spate} \leq UP_{at} \left( \sum_{w \in W} Y A_{put} \right) \tag{24}
\]

\[
\quad \forall a \in A, t \in T, p \in P,
\]
Constraint (24) indicates the time window for receiving raw materials by production centers in each time period.

\[ LC_{cr} \leq \sum_{g \in G} \sum_{d \in D} TDC_{deg} ZB_{dcr} \leq UC_{cr} \quad \forall r \in R, t \in T, \]  

(25)

Constraint (25) indicates the time window for receiving products by distribution centers in each time period.

\[ \sum_{d \in D} \sum_{f \in F} XB_{pdrt} \leq \sum_{w \in W} XP_{prt}w \quad \forall r \in R, t \in T, p \in P, \]  

(26)

Constraint (26) indicates that the volume of the product sent by production centers to distribution centers should be less than or equal to its production volume in each period of each product.

\[ YA_{put}, YB_{dt}, YC_{mt}, YD_{q}, YE_{ot}, \omega A_{space}, \omega B_{dcr} \in \{0, 1\}, \]  

\[ XF_{prtw}, XA_{space}, XB_{pdrt}, XC_{dcr}, XD_{cmrth}, XF_{morth}, XG_{opath} \geq 0, \]  

\[ IN_{drt}, BO_{drt} \geq 0 \quad \forall p \in P, w \in W, t \in T, m \in M, q \in Q, o \in O, s \in S, a \in A, r \in R, \]  

(27)

\[ e \in E, f \in F, g \in G, h \in H. \]

Constraint (27) specifies the domain of the variables.

3.2. **Robust mathematical model.** RO methods offer a risk-averse approach to dealing with uncertainties in optimization problems. They have attracted a lot of attention as an efficient tool to cope with real-world uncertainty [27, 34]. Based on Pishvaee et al. [42], a solution is called robust if it is feasible and optimally robust simultaneously. Feasibility means that the proposed solution must get feasible values of the uncertain parameters, and optimally robust means that the value of the objective function for (almost) all values of the uncertain parameters remains close to the optimal value or minimum or, at least, has the less deviation from the optimal value.

In this research, the RO approach of Bertsimas and Sim is employed due to the development of a linear mathematical model and for considering the level of controllable conservatism close to real-world conditions.

The Bertsimas and Sim’s model is further explained for the linear optimization problem in which the objective function is minimization and the uncertainty coefficients exist in both the objective function and the constraints.

The optimization problem is assumed as follow:

\[
\begin{align*}
\text{minimize} & \quad C^T X \\
\text{subject to} & \quad AX \leq b, \\
& \quad l \leq X \leq u.
\end{align*}
\]  

(28)

Also, uncertainty levels are defined as:

Each of the constraint coefficients \( a_{ij}, j \in N = 1, 2, ..., n \) is modelled as an independent random variable with symmetrical but unknown distribution \( \tilde{a}_{ij}, j \in N \). They take value in the interval \([a_{ij} - \tilde{a}_{ij}, a_{ij} + \tilde{a}_{ij}]\), where \( \tilde{a}_{ij} \) stands for the deviation from the nominal coefficient \( a_{ij} \). Similarly, each of the objective coefficients \( c_j, j \in N \) take value in the interval \([c_j - d_j, c_j + d_j]\), where \( d_j \) is the deviation from the nominal coefficient \( c_j \). Since the objective function is of minimization and the goal of robust models is to provide the maximum regret, only one side of the
proposed interval is considered. Accordingly, it is supposed that $c_j$ takes value in $[c_j, c_j + d_j]$.

To model the robust counterpart of the problem, $\Gamma_i$ is denoted as below:

Consider constraint $i$ as $a_i^T x \leq b_i$. Here, $J_i$ is denoted as a set of uncertain coefficients in row $i$. For each constraint row of $i$, a parameter of $\Gamma_i$ (an integer or non-integer number) is defined such that $[0, |J_i|]$. In other words, the role of $\Gamma_i$ in constraints is to justify the robustness of the suggested approach and conservatism level of the solution. It has been proven that it is unlikely that all coefficients become uncertain simultaneously [8]. Therefore, it can change up to the maximum value of $\Gamma_i - \lfloor \Gamma_i \rfloor$. In other words, only a subset of coefficients is allowed to affect the solutions adversely. With this assumption, it is ensured that if the same condition happens actually, the optimally robust solution will be feasible definitely. Also, due to the symmetric distribution of the variables, even if the number of changing coefficients exceeds $\lfloor \Gamma_i \rfloor$, the optimal solution will be still feasible with a very high probability. Therefore, $\Gamma_i$ is considered as the protection level for constraint $i$.

Here, $\Gamma_0$ controls the robustness level in the objective function. Therefore, it is intended to determine the optimal solutions when $\Gamma_0$ number of coefficients are changed in the objective function and have the most significant effect on the solution. Generally, higher values of $\Gamma_0$ raise the conservatism level against the higher cost it should be paid in the objective function. Here, $\Gamma_0$ is necessarily an integer number but the rest of $\Gamma_i$ can be integer or non-integer.

On this basis, the nominal linear robust counterpart of the problem is obtained as below [8]:

$$\begin{align*}
\text{minimize} & \quad C^T X + \max_{s_0|s_0 \subseteq J_0, |s_0| \leq \Gamma_0} \left\{ \sum_{j \in s_0} d_j |x_j| \right\} \\
\text{subject to} & \\
\sum_{j \in J} a_{ij} x_j + \max_{s_i \cup \{t_i\}|s_i \subseteq J_i, |s_i| \leq |\Gamma_i|, t_i \in J_{ns_i}} \left\{ \sum_{j \in s_i} \hat{a}_{ij} |x_j| + (\Gamma_i - |\Gamma_i|)\hat{a}_{it_i} |x_{t_i}| \right\} & \leq b_i \quad \forall i \in J
\end{align*}$$

(29)

To transform the model into a linear optimization model, Lemma 3.1 is needed.

**Lemma 3.1.** For the vector $x^*$, the protection level of constraint $i$ is calculated through Equation (30).

$$\beta_i(x^*, \Gamma_i) = \max_{s_i \cup \{t_i\}|s_i \subseteq J_i, |s_i| \leq |\Gamma_i|, t_i \in J_{ns_i}} \left\{ \sum_{j \in s_i} \hat{a}_{ij} |x^*_j| + (\Gamma_i - |\Gamma_i|)\hat{a}_{it_i} |x^*_{t_i}| \right\} \quad \forall i \in J$$

(30)

which is equal to the optimum value of the objective function of Model (31):

$$\beta_i(x^*, \Gamma_i) = \max_{j \in J_i} \sum_{j \in J_i} \hat{a}_{ij} |x^*_j| z_{ij}$$

subject to
\[
\sum_{j \in J_i} z_{ij} \leq \Gamma_i \quad \forall i \in I, \\
0 \leq z_{ij} \leq 1 \quad \forall i, j \in J_i,
\]

(31)

Lemma (3.1) has been proven in Bertsimas and Sim [8].

By inserting the dual of Model (32) in the robust counterpart model, it is formulated as follow:

\[
\text{minimize } C^T X + z_0 \Gamma_0 + \sum_{j \in J_0} p_{0j} \\
\text{subject to } \\
\sum_{j \in J} a_{ij} x_j + z_i \Gamma_i + \sum_{j \in J_i} p_{ij} \leq b_i \quad \forall i \in I, \\
z_0 + p_{0j} \geq d_j y_j \quad \forall j \in J_0, \\
z_i + p_{ij} \geq a_{ij} y_j \quad \forall i \neq 0, j \in J_i, \\
p_{ij} \geq 0 \quad \forall i, j \in J_i, \\
y_j \geq 0 \quad \forall j \in J_i, \\
z_i \geq 0 \quad \forall i \in J_i, \\
-y_j \leq x_j \leq y_j \quad \forall j \in J_i, \\
l_j \leq x_j \leq u_j \quad \forall j \in J_i.
\]

(32)

In the proposed mathematical model, the customer demand \((DE_{crt})\), flow rate of returned product type \(r\) from customer \(c\) in each period \((\alpha_{rc})\) and flow rate of disposable product type \(r\) transferable from collection centers to disposal centers \((\beta_r)\) and flow rate of recoverable product type \(r\) transferable from collection centers to recovery centers \((1 - \beta_r)\) are the main parameters of the problem with uncertain nature, which is defined in an uncertainty interval. Based on the Bertsimas’ and Sim’s approach, the uncertainty intervals are \([(\overline{DE}_{crt} - \overline{DE}_{crt}), (\overline{DE}_{crt} + \overline{DE}_{crt})], (\overline{\alpha}_{rc}, \overline{\alpha}_{rc} + \overline{\alpha}_{rc})\), \((\overline{\beta}_r, \overline{\beta}_r + \overline{\beta}_r)\), and \([(1 - \overline{\beta}_r) - (1 - \overline{\beta}_r), (1 - \overline{\beta}_r) + (1 - \overline{\beta}_r)]\).

Regarding the uncertain interval space, each of uncertain \(DE_{crt}\) is in a symmetric and bounded distance with the center of \(\overline{DE}_{crt}\) and in the form of \(\overline{DE}_{crt} = \rho \overline{DE}_{crt}\). In this equation, \(\overline{DE}_{crt}\) is the estimated value of customer demand, \(DE_{crt}\) is the fluctuation of demand and \(\rho > 0\) is the uncertainty level. Likewise, \(\alpha_{rc}\) and \(\beta_r\) would be in the form of \(\alpha_{rc} = \rho \alpha_{rc}\) and \(\beta_r = \rho \beta_r\), respectively.

In the proposed mathematical model, Constraints (10), (14)-(16) have led to uncertainty due to the existence of uncertain parameters. Thus, these constraints should become robust based on the offered model of Bertsimas and Sim. As a result, the modeling of the proposed robust model is presented as follows. Constraint (33) is presented as an alternative to Constraint (10) to provide robust conditions:

\[
\sum_{c \in C} (\overline{DE}_{crt} - \Gamma_{crt} \overline{DE}_{crt}) \leq IN_{drt-1} + \sum_{g \in G, c \in C} X C_{dcertg} + BO_{drt} - IN_{drt} \\
\leq \sum_{c \in C} (\overline{DE}_{crt} + \Gamma_{crt} \overline{DE}_{crt}) \quad \forall d \in D, r \in R, t \in T.
\]

(33)

Moreover, the conservatism level (uncertainty budget) of Constraint (33) is equal to \(\Gamma_{crt} \in [0, 1]\), which has a similar definition to the Bertsimas and Sim’s model. Constraints (34)-(37) are also presented to provide the robust condition in Constraint.
Likewise, conservatism level (uncertainty budget) of Constraint (38) is equal to 
\[ \beta_r \left( \sum_{d \in D} \sum_{t \in G} X C_{d \rightarrow t} \right) - z_{rct}^{\prime} \Gamma_{rct}^{\prime} - \sum_{d \in D} \sum_{g \in G} P_{d \rightarrow t} \leq \sum_{m \in M} \sum_{h \in H} X D_{cmrth} \]
(34)
\[
\leq \beta_r \left( \sum_{d \in D} \sum_{t \in G} X C_{d \rightarrow t} \right) + z_{rct}^{\prime} \Gamma_{rct}^{\prime} + \sum_{d \in D} \sum_{g \in G} P_{d \rightarrow t} \quad \forall r, c, t,
\]
(35)

\[ z_{rct} + P_{d \rightarrow t} \geq \beta_r E_{dtg} \quad \forall c \in C, d \in D, g \in G, r \in R, t \in T, \]
(36)

\[ - E_{dtg} \leq X C_{d \rightarrow t} \leq E_{dtg} \quad \forall c \in C, d \in D, g \in G, r \in R, t \in T, \]
(37)

Furthermore, conservatism level (uncertainty budget) of Equation (31) is equal to \( \Gamma_{rct}^{\prime} \in [0, |R|, |C|, |T|] \), which has a similar definition to the Bertsimas's and Sim's model. Constraints (38)-(41) are presented to provide the robust condition in Constraint (15):

\[ \beta_r \left( \sum_{c \in C} \sum_{m \in M} \sum_{h \in H} X D_{cmrth} \right) - z_{rct}^{\prime} \Gamma_{rct}^{\prime} - \sum_{c \in C} \sum_{m \in M} \sum_{h \in H} P_{cmrth}^{\prime} \leq \sum_{q \in Q} \sum_{m \in M} \sum_{h \in H} X E_{cmrth} \]
(38)
\[
\leq \beta_r \left( \sum_{c \in C} \sum_{m \in M} \sum_{h \in H} X D_{cmrth} \right) + z_{rct}^{\prime} \Gamma_{rct}^{\prime} + \sum_{c \in C} \sum_{m \in M} \sum_{h \in H} P_{cmrth}^{\prime} \quad \forall r \in R, t \in T,
\]
(39)

\[ z_{rct}^{\prime} + P_{cmrth}^{\prime} \geq \beta_r E_{cmrth}^{\prime} \quad \forall c \in C, m \in M, r \in R, t \in T, h \in H, \]
(40)

\[ - E_{cmrth}^{\prime} \leq X D_{cmrth} \leq E_{cmrth}^{\prime} \quad \forall c \in C, m \in M, r \in R, t \in T, h \in H, \]
(41)

Likewise, conservatism level (uncertainty budget) of Constraint (38) is equal to \( \Gamma_{rct}^{\prime} \in [0, |R|, |T|] \), which has a similar definition to the Bertsimas’s and Sim’s model. Finally, Constraints (42)-(45) are presented to provide the robust condition in Constraint (16):

\[ (1 - \beta_r) \left( \sum_{c \in C} \sum_{m \in M} \sum_{h \in H} X D_{cmrth} \right) - z_{rct}^{\prime \prime} \Gamma_{rct}^{\prime \prime} - \sum_{c \in C} \sum_{m \in M} \sum_{h \in H} P_{cmrth}^{\prime \prime} \leq \sum_{o \in O} \sum_{m \in M} \sum_{h \in H} X F_{cmrth} \]
(42)
\[
\leq (1 - \beta_r) \left( \sum_{c \in C} \sum_{m \in M} \sum_{h \in H} X D_{cmrth} \right) + z_{rct}^{\prime \prime} \Gamma_{rct}^{\prime \prime} + \sum_{c \in C} \sum_{m \in M} \sum_{h \in H} P_{cmrth}^{\prime \prime} \quad \forall r \in R, t \in T,
\]
(43)

\[ z_{rct}^{\prime \prime} + P_{cmrth}^{\prime \prime} \geq (1 - \beta_r) E_{cmrth}^{\prime \prime} \quad \forall c \in C, m \in M, r \in R, t \in T, h \in H, \]
(44)

\[ - E_{cmrth}^{\prime \prime} \leq X D_{cmrth} \leq E_{cmrth}^{\prime \prime} \quad \forall c \in C, m \in M, r \in R, t \in T, h \in H, \]
(45)

Likewise, conservatism level (uncertainty budget) of Constraint (42) is equal to \( \Gamma_{rct}^{\prime \prime} \in [0, |R|, |T|] \), which has a similar definition to the Bertsimas’s and Sim’s model. It is used jointly with Constraint (33) due to the existence of a similar parameter of uncertainty. Ultimately, the robust mathematical model is obtained by replacing Constraint (34) with Constraint (10), Constraints (34)-(37) with Constraint (14), Constraints (38)-(41) with Constraint (15), and Constraints (42) to (45) with Constraint (16).
4. Exact solution method: $\epsilon$-constraint. The $\epsilon$-constraint technique is among one of the most applicable multi-objective decision-making (MODM) methods to cope with the multi-objectiveness of the problems. The Pareto front can be drawn by the $\epsilon$-constraint method including non-dominated Pareto solutions. By considering the values of for each sub-objective function, the problem can be solved. For the proposed problem, the $\epsilon$-constraint method is employed through Model (46).

$$\begin{align*}
\text{minimize } & f_1(x) \\
\text{subject to } & x \in X, \\
& f_2(x) \leq \epsilon_2, \\
& \vdots \\
& f_n(x) \leq \epsilon_n.
\end{align*}$$

(46)

The main steps in the $\epsilon$-constraint method are as follows:

i. Considering one of the objectives as the main objective function,
ii. Based on each objective function, the problem is solved. Then, the optimal values of objective functions are obtained.
iii. The difference between the two optimal values of the second objective function is divided into several pre-determined parts. A table of values $\epsilon_2, \ldots, \epsilon_n$ is then generated.
iv. The problem is solved by the main objective function and $\epsilon_2, \ldots, \epsilon_n$,
v. Pareto solutions are reported.

5. Meta-heuristic algorithm: NSGA-II. Non-dominated Sorting Genetic Algorithm (NSGA) is one of the most popular and widely used algorithms in the field of multi-objective optimization for treating multi-objective problems, which was introduced by Deb et al. [15]. Since then, many researchers have been applying NSGA-II to different practical multi-objective optimization problems [44, 51].

Besides the functionality of NSGA-II, it can be considered as standard for many other multi-objective optimization algorithms. The unique approach of NSGA-II in dealing with multi-objective optimization problems has been used over and over to create a novel algorithm. Undoubtedly, this algorithm is one of the most basic multi-objective evolutionary optimization algorithms and so, it is employed in this research.

In this study, in addition to presenting a multi-objective MILP model, an NSGA-II is also developed. Therefore, in this section, the implementation of the algorithm, operators, and generation of solutions are explained. The flowchart of the proposed NSGA-II is given by Figure 2.

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 displays the locations and the second part specifies the volume of distribution of products. In the first part, the values are between 0 and 1. In each cell, if the value is more than 0.05, 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 Table 2. In this example, there are 3 distribution centers and 5 customers.

According to Table 2, distribution centers 2 and 3 are established. The percentage of distribution from distribution centers 2 and 3 can be normalized to determine the amount of demand. Therefore, the interpretation of the chromosome is presented in Table 3.

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. After calculating the fitness function, the solutions are categorized. Thus, among a set of points, a number of them are considered as non-dominated to the others. In this way, several levels or fronts can be formed, and if needed, some of these levels are selected for the next steps and the rest are removed. Crossover and mutation operators are then used to generate the next generation. For the
mutation operator, the single-point approach is used. Afterward, the parameters of the NSGA-II are adjusted. For this purpose, different values are considered for each parameter according to Table 4. Then, using the trial and error method based on the values of the objective function, the best value for each of them is obtained and reported in Table 5.

Table 2. An example of chromosome

| First Part | 0.41 | 0.72 | 0.93 |
|------------|------|------|------|
| Second Part | Customer 1 | Customer 2 | Customer 3 | Customer 4 | Customer 5 |
| Distribution Center 1 | 0.61 | 0.29 | 0.43 | 0.27 | 0.35 |
| Distribution Center 2 | 0.45 | 0.73 | 0.28 | 0.34 | 0.19 |
| Distribution Center 3 | 0.35 | 0.91 | 0.73 | 0.58 | 0.39 |

Table 3. Interpretation of chromosome

| First Part | 0 | 1 | 1 |
|------------|---|---|---|
| Second Part | Customer 1 | Customer 2 | Customer 3 | Customer 4 | Customer 5 |
| Distribution Center 1 | 0 | 0 | 0 | 0 | 0 |
| Distribution Center 2 | 0.52 | 0.44 | 0.27 | 0.37 | 0.32 |
| Distribution Center 3 | 0.48 | 0.56 | 0.73 | 0.63 | 0.68 |

Table 4. The value of parameters for NSGA-II

| Parameter       | Value |
|-----------------|-------|
| Npop            | 50    |
| Max iteration   | 100   |
| Cross rate      | 0.5   |
| Mut rate        | 0.5   |

Table 5. The optimal value of parameters of NSGA-II

| Parameter      | Value |
|----------------|-------|
| Npop           | 100   |
| Max iteration  | 200   |
| Cross rate     | 0.7   |
| Mut rate       | 0.3   |
6. 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.

6.1. Validation of the proposed model and algorithm. In order to assess the validation of the NSGA-II, a number of problem instances are generated in small size to be solved by the proposed metaheuristic algorithm and $\epsilon$-constraint method. The number of each center is reported in Table 6.

| Set                      | Number |
|--------------------------|--------|
| Suppliers                | 4      |
| Production centers       | 3      |
| Distribution centers     | 3      |
| Customers                | 5      |
| Collection centers       | 2      |
| Recovery centers         | 2      |
| Disposal centers         | 2      |
| Products                 | 2      |
| Raw materials            | 2      |
| Time periods             | 1      |
| Technology levels        | 2      |
| Transportation modes     | 2      |

Also, the other parameters of the problem are randomly generated with a uniform distribution according to Table 7.

| Parameter                                                      | Value               |
|----------------------------------------------------------------|---------------------|
| Customer demand                                               | U(1,200)            |
| Quantity of raw material                                       | U(50,350)           |
| Capacity of suppliers                                         | U(1000,2500)        |
| Capacity of production centers                                 | U(500,2000)         |
| Capacity of distribution centers                               | U(1000,2500)        |
| Capacity of collection centers                                 | U(1000,2500)        |
| Capacity of disposal centers                                  | U(1000,2000)        |
| Capacity of recovery centers                                  | U(1000,2000)        |
| Cost of transporting raw materials from the supply center to the production center | U(50,150)           |
| Cost of transporting products from production center to distribution center | U(50,150)           |
| Cost of transporting from distribution center to customer      | U(50,150)           |
| Cost of transporting from customer to collection center         | U(50,150)           |
| Cost of transporting from the collection center to the disposal center | U(50,150)           |
| Parameter                                                                 | Value               |
|--------------------------------------------------------------------------|---------------------|
| Cost of transporting from the collection center to the recovery center    | U(50,150)           |
| Cost of transporting from the recovery center to the production center   | U(50,150)           |
| Volume of CO$_2$ emission released to transport raw material from the supply center to the production center | U(50,100)           |
| Volume of CO$_2$ emission released to transport products from the production center to the distribution center | U(50,100)           |
| Volume of CO$_2$ emission released to transport from the distribution center to the customer | U(50,100)           |
| Volume of CO$_2$ emission released to transport from customer to the collection center | U(50,100)           |
| Volume of CO$_2$ emission released to transport from the collection center to the disposal center | U(50,100)           |
| Volume of CO$_2$ emission released to transport from the collection center to the recovery center | U(50,100)           |
| Volume of CO$_2$ emission released to transport from the recovery center to the production center | U(50,100)           |
| Preparation time for transportation of raw material from the supply center to production center | U(10,20)            |
| Preparation time for the transportation of products from distribution center to customers | U(10,20)            |
| Distance between supply center and production center                     | U(500,1500)        |
| Distance between production center and distribution center               | U(500,1500)        |
| Distance between the distribution center and customer                    | U(500,1500)        |
| Distance between customer and collection center                          | U(500,1500)        |
| Distance between collection center and disposal center                   | U(500,1500)        |
| Distance between collection center and recovery center                   | U(500,1500)        |
| Distance between recovery center and production center                   | U(500,1500)        |
| Production cost in production centers                                    | U(50,100)          |
| Processing cost in distribution centers                                  | U(50,100)          |
| Processing cost in production centers                                    | U(50,100)          |
| Processing cost in disposal centers                                     | U(50,100)          |
| Processing cost in recovery centers                                     | U(50,100)          |
| Fixed cost of establishing a production center                           | U(5000,15000)      |
| Fixed cost of establishing a distribution center                         | U(5000,15000)      |
The above problem is implemented by NSGA-II and $\epsilon$-constraint approach in MATLAB and GAMS/CPLEX solver, respectively. The uncertainty levels are set to 0.2. The mean CPU times of NSGA-II and $\epsilon$-constraint method are about 14 and 40 seconds. The obtained Pareto solutions are presented in Table 8.

**Table 8.** Results of the solution methods for the robust model.

| No. | NSGA-II | EC |
|-----|---------|----|
|     | Objective 1 | Objective 2 | Objective 1 | Objective 2 |
| 1   | 860870 | 26703 | 860824 | 26700 |
| 2   | 861031 | 26288 | 861029 | 26277 |
| 3   | 864920 | 25883 | 864875 | 25854 |
| 4   | 869473 | 25445 | 869468 | 25441 |
| 5   | 874268 | 25014 | 874115 | 25010 |

According to Figure 3, the red dots show the solutions obtained by the NSGA-II and the blue dots show the solutions gained by the $\epsilon$-constraint method. Regarding Table 8 and Table 3, the difference between the solutions of the two methods is very nominal, which indicates the appropriate performance of the proposed meta-heuristic algorithm.

6.2. **Deterministic model vs. robust model.** Here, to investigate the impact of robustness, a comparison is made between the deterministic and robust model and the obtained results are given in terms of the mean value of the objective functions and mean CPU time. Table 9 represents the results obtained by the proposed NSGA-II and the $\epsilon$-constraint approach.

**Table 9.** Results of the solution methods for deterministic and robust models.

| Model   | NSGA-II | EC |
|---------|---------|----|
|         | Objective 1 | Objective 2 | CPU time | Objective 1 | Objective 2 | CPU time |
| Deterministic | 858651.6 | 25271.3 | 12.94 | 858242.1 | 24971.3 | 31.84 |
| Robust   | 866112.4 | 25866.6 | 14.04 | 866062.2 | 25856.4 | 40.56 |
According to Table 9, it is revealed that the deterministic model yields better solutions without ensuring robustness. In other words, although the objective functions and CPU time take higher values in the proposed robust model, the robustness of the solutions under the uncertainty is not guaranteed by the deterministic model. On the other hand, the proposed NSGA-II could provide acceptable solutions in comparison with the $\epsilon$-constraint method in both deterministic and robust models.

6.3. **Validation of model and the proposed algorithm in large size.** In this section, using Table 7 and Table 10, four other problems are generated in the medium and large size to evaluate the performance and efficiency of the proposed algorithm in comparison with the exact method.

**Table 10.** Information of the problem instances in medium- and large- size

| Sets                  | P1  | P2  | P3  | P4  |
|-----------------------|-----|-----|-----|-----|
| Suppliers             | 8   | 15  | 20  | 40  |
| Production centers    | 5   | 10  | 15  | 25  |
| Distribution centers  | 5   | 10  | 15  | 30  |
| Customers             | 8   | 20  | 35  | 50  |
| Collection centers    | 4   | 6   | 10  | 15  |
| Recovery centers      | 4   | 6   | 10  | 15  |
| Disposal centers      | 4   | 6   | 10  | 15  |
| Products              | 4   | 6   | 10  | 15  |
| Raw materials         | 4   | 6   | 10  | 15  |
| Time periods          | 3   | 4   | 5   | 8   |
| Technology levels     | 3   | 4   | 5   | 8   |
| Transportation modes  | 3   | 4   | 5   | 8   |

For better validation of the proposed algorithm and its capability to identify the optimal Pareto front, four criteria specific to multi-objective algorithms are
used. Due to this, the four criteria of mean ideal distance (MID), diversity metric (DM), spacing metric (SM), and the number of Pareto solutions (NPS) are calculated. Then, according to the values of these criteria, the performance of the offered 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 [47]. The values of criteria calculated for the problems in different uncertainty levels are presented in Tables 11-13.

Table 11. The average value of criteria for the two algorithms in the uncertainty level of 0.2

| Criteria       | DM  | MID  | SM  | NPS |
|----------------|-----|------|-----|-----|
| Problem/Method | EC  | NSGA-II | EC  | NSGA-II | EC  | NSGA-II | EC  | NSGA-II |
| 1              | 1.09| 1.13 | 0.82| 0.88| 1.12| 1.01 | 4   | 8    |
| 2              | 1.23| 1.2  | 1.13| 1.09| 1.07| 0.99 | 2   | 14   |
| 3              | 0.92| 0.95 | 0.94| 0.9 | 0.71| 0.66 | 3   | 23   |
| 4              | -   | 1.13 | -   | 1.55| -   | 2.39 | -   | 32   |

Table 12. The average value of criteria for the two algorithms in the uncertainty level of 0.4

| Criteria       | DM  | MID  | SM  | NPS |
|----------------|-----|------|-----|-----|
| Problem/Method | EC  | NSGA-II | EC  | NSGA-II | EC  | NSGA-II | EC  | NSGA-II |
| 1              | 1.03| 1.09 | 0.86| 0.74| 2.33| 2.14 | 3   | 7    |
| 2              | 1.16| 1.21 | 0.93| 0.82| 2.02| 1.91 | 2   | 16   |
| 3              | 0.75| 0.69 | 0.79| 0.83| 0.72| 0.92 | 2   | 28   |
| 4              | -   | 1.31 | -   | 1.02| -   | 1.24 | -   | 43   |

Table 13. The average value of criteria for the two algorithms in the uncertainty level of 0.5

| Criteria       | DM  | MID  | SM  | NPS |
|----------------|-----|------|-----|-----|
| Problem/Method | EC  | NSGA-II | EC  | NSGA-II | EC  | NSGA-II | EC  | NSGA-II |
| 1              | 1.17| 1.24 | 0.59| 0.69| 1.25| 1.03 | 2   | 6    |
| 2              | 0.84| 0.93 | 0.32| 0.23| 1.97| 1.51 | 4   | 15   |
| 3              | 1.2 | 1.31 | 0.43| 0.31| 0.9 | 0.87 | 2   | 37   |
| 4              | -   | 0.71 | -   | 0.92| -   | 2.34 | -   | 52   |

According to Tables 11-13, the proposed NSGA-II 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 can be employed to solve large-size problems. More specifically, the NSGA-II performs much better than the EC in terms of Diversity criteria. This means that NSGA-II can generate Pareto fronts with a wider range of possible solutions.
In terms of MID, the NSGA-II 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 SM, the performance of the NSGA-II has been much more appropriate and it has produced a more uniform front than EC. Besides, the NSGA-II has always managed to find more Pareto solutions.

For further comparison of the algorithms, the simple additive weighting (SAW) method is employed. First, all the values of criteria are normalized. Next, the average value of the criteria is calculated (with the same weight) for each algorithm in each problem such that it considers them as the efficacy of that algorithm in that problem. The execution steps of SAW are given as follows:

Step 1: Nature of indexes must be identified according to its positiveness or negativeness.

Step 2: Values computed for measures in the decision matrix are descaled in Equations (47)-(48):

For negative criteria: \( n_{ij} = \frac{r_{ij}}{r_{ij}^\text{min}}, \quad i = 1,2,\ldots,m; j = 1,2,\ldots,n, \) \( (47) \)

For positive criteria: \( n_{ij} = \frac{r_{ij}}{r_{ij}^\text{max}}, \quad i = 1,2,\ldots,m; j = 1,2,\ldots,n. \) \( (48) \)

Step 3: By taking into account the importance coefficients or weight of measures and normalized values of the decision matrix, SAW can be computed for each experiment according to Equations (49)-(50):

\[
\sum_{j=1}^{n} w_j = 1 \quad (49)
\]

\[
\text{SAW}_i = \sum_{j=1}^{n} w_j n_{ij}, \quad i = 1,2,\ldots,m. \quad (50)
\]

These evaluations are presented in Figures 4-6 for the uncertainty levels of 0.2, 0.4, and 0.5. Accordingly, the proposed NSGA-II performs highly close to the exact method.

However, since the EC method has failed to solve the large-size problems (Problem 4) exactly, the proposed NSGA-II is employed. Therefore, the proposed NSGA-II is the best tool to cope with large-size problems and the EC method lacks the necessary efficiency.

Figure 7 also represents the solution time for solving different categories of the problem. According to Figure 7, by rising the size of problems, the exact solution time has increased dramatically until the EC is not able to solve Problem 4 exactly within the proposed time limit. On the other hand, the proposed NSGA-II can solve the problems in a much shorter time. All in all, the NSGA-II needs less time to discover the Pareto solutions which be considered as another advantage of this algorithm.

According to the obtained results, it can be inferred that the proposed NSGA-II is an efficient tool to deal with the proposed network. Managers may consider this algorithm to tackle the complexity of problem in the real-world and even extend it to other developed problems in a given network. For example, if other assumptions or limitations are incorporated into the problem, the flexibility of the algorithm plays a key role in providing a feasible-robust-optimal solution.
Figure 4. The comparison of NSGA-II and EC at uncertainty level 0.2

Figure 5. The comparison of NSGA-II and EC at uncertainty level 0.4

Figure 6. The comparison of NSGA-II and EC at uncertainty level 0.5
7. Conclusion and future works. This study addressed a green CLSC related to the production and distribution of the perishable product was designed under uncertainty. The main contribution is the design of a backup decision system for planning the supply, production, and distribution of perishable products taking into account major real-world assumptions such as different levels of technology and approved time windows for the distribution of products using vehicles with a suitable cooling system. On the other hand, an RO approach was utilized to cope with the problem uncertainty. The main objectives of the problem were to minimize the total cost of the network and the total volume of emissions at the chain levels. To tackle the complexity of the offered model, a NSGA-II was developed. Furthermore, the GAMS/CPLEX solver and \( \varepsilon \)-constraint method were used as an exact method to solve the problem and prove the correctness and validation of the model. After studies and comparisons made by the two proposed research methods, it was found that the proposed algorithm covers a wider range of solutions and the quality of the solutions is higher and produces a more uniform front. Also, the solution time of the proposed NGSA-II was significantly shorter compared to the exact method. One of the notable points was the increase of objective functions by increasing the level of uncertainty, which was observed in all categories. Based on the main limitations of the study, the following suggestions are given for future research direction:

i. Developing other multi-objective meta-heuristic algorithms to be compared with the proposed NSGA-II, such as Multi-Objective Particle Swarm Optimization (MOPSO) algorithm [44], Multi-Objective Stochastic Fractal Search (MOSFS) algorithm [29] and Multi-Objective Grey Wolf Optimizer (MOGWO) algorithm [30].

ii. Applying other uncertainty techniques to be compared with the proposed RO approach, such as fuzzy programming [20, 52] and stochastic optimal control [57],

iii. Studying the sustainable development in the problem by addressing the social aspect of the proposed CLSC network [1, 36].
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