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An enhanced robust possibilistic programming approach for forward distribution network design with the aim of establishing social justice: A real-world application

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Abstract

The business environment, especially in the supply chain, is virtually fluctuating and is entangled with a lot of problems. Accordingly, a tailored mechanism should be adopted to deal with these problems. To do so, supply chains must take precautionary measures such as storing products and holding safety stock, etc. Given the importance of storage in supply chains, warehouses and depots should be carefully taken into account and located in such a way that their best performance is warranted. In this regard, this paper addresses a robust Multi-Objective multi-product model to design a distribution system under operational risks and disruption considerations. In the proposed model, the objective functions include minimizing the total distribution system cost, the total environmental impacts caused by supply chain along with minimizing the maximum lost sales in customer zones, while taking into consideration possible complete multiple disruptions in facilities and routes between them. Besides, a ε-constraint method is utilized to convert the Multi-Objective problem to a single objective model. In this paper, a two-stage robust possibilistic programming approach is deployed to cope with the uncertainty and disruption risks in the proposed model. Eventually, a real automotive case study is applied to the proposed model, via which the applicability and performance of the proposed model are endorsed. Results indicate that considering operational and disruption risks in the supply chain using two-stage robust optimization will require high costs but it will lead to economic savings and technical advantages in the long term.

Keywords: Warehouse, robust optimization, uncertainty, fuzzy logic, disruption, distribution network design.

1- Introduction

A distribution chain is a system, consisting of suppliers, warehouses, depots, distribution centers (DC), retailers, and customers. More precisely, in a distribution system, products are supplied, transported, and delivered to customers to meet specific objectives such as minimizing total distribution cost, total distance traveled, etc. Thus, an efficient distribution network management can remarkably improve the system performance by reducing the total system costs and rectifying competitive conditions in the business environment (Ouhimmou et al, 2019). The distribution system

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design problem predominantly encompasses location-allocation decisions and routing sub-problem. Relevant studies include determining optimal shipping routes from supply nodes to demand nodes so that customers' demands are fulfilled, and the total distribution costs including inventory, shortages, facilities, and transportation costs are minimized (Abareshi & Zaferanieh, 2019; Diabat et al, 2017).

Nowadays, warehouses have a substantial share of costs in the distribution network. In this manner, supply chain management is interested in investigating the location of this component in the logistics network (Le et al, 2019). Warehouses have a direct effect on operational costs in manufacturing systems and also can impress on demand levels in service chains. Warehouses and depots are one of the most outstanding components and echelons of the distribution network (Reyes et al, 2019). Accordingly, they should be carefully taken into account and located in such a way that their best performance is warranted. Indeed, by optimizing a distribution network design problem, optimal location and allocation decisions can be made for warehouses and depots. Given the fact that the business environment is virtually fluctuating and also is entangled with a lot of difficult conditions, the planning of the distribution will be troublesome and costly for companies. Distribution systems may also confront shortages in such cases (Abdel-Basset et al, 2019). As regards any shortage of products in customer zones eventuates in the dissatisfaction as well as reducing company credit, an expedient program should be adopted to deal with uncertainty and prevent shortages (DuHadway et al, 2019). One of the essential principles of designing an efficient distribution network is to observe environmental aspects and create less pollution in the transportation process, holding, operations, etc. Due to the global warming and the need for environmental conservation, supply chain network design needs to be green to minimize environmental damage in addition to achieving minimum cost (Rad & Nahavandi, 2018).

In accordance with the above-mentioned discussions, some corrective actions have been taken to enhance the performance of the distribution network in this study as follows. Given the significance of product shortage in the distribution network, the shortage variable was defined for customer zones, and also the unit cost of the shortage was considered to be a high deficit to reduce the lost sales. As mentioned before, there is a need to optimize transportation, holding, operational, and establishment processes to reduce air pollution and take into account environmental considerations. To this end, we try to manage the distribution system in a way that minimizes the total environmental impact. This article is also able to establish social justice by minimizing the maximum lost sales in customer zones. a two-stage robust possibilistic programming (TSRPP) approach is employed to cope with operational and disruption risks in the proposed model. Notably, robust optimization fortifies model to determine stable decisions for the investigated supply chain. Also, all possible disruptions risks in the investigated supply chain are considered using discrete and independent scenarios and counteracted by a two-stage modeling approach. It is notable to say that disruptions risks are considered in facilities and routes between them. Lastly, a real-world automotive case study is applied to appraise the applicability and performance of the study framework.

This paper is organized as follows. In section 2, we review pertinent literature on distribution network design, as well as stochastic, robust, and fuzzy programming models. Next, in Section 3, we state the problem and propose MILP mathematical formulation. Section 4 explains the solution method to solve the mathematical model. In section 5, the computational results of the model execution based on a real-world case study are presented. Finally, conclusions are provided, and avenues for further research are suggested in section 6.

2- literature review

In this section, a review of relevant researches in the area of facility location-allocation problems (FLAP) and supply chain network design (SCND) under operational and disruption risks are wisely provided. For a detailed overview of FLAP and distribution network design, please see (Farahani et al, 2013; Klose & Drexl, 2005b; Melo et al, 2009). Jafari et al (2010b) proposed a Multi-Objective model in distribution centers location-allocation problems using fuzzy programming. The relationship between distribution facilities is considered in this study. Klose & Drexl (2005b) introduced a facility location model for designing an efficient distribution system. Facility location-allocation decisions cover the core topics of distribution system design. Barreto et al (2007b) proposed a facility location-routing problem (LRP) based on a clustering approach. The FLRP includes both facility location-allocation and vehicle routing decisions simultaneously. In this study, they considered a two-level distribution system design and aimed to determine distribution centers and routes among them. Prins et al (2007b) used a hybrid Lagrangian relaxation algorithm to solve an FLRP. They aimed to minimize distribution system cost along with determining optimal routing decisions. (Chen et al, 2008) aimed to solve an FLP using a combination of the ant colony and Lagrangian relaxation algorithms. Lin (2009b) presented a FLAP considering customer service level concerns under uncertainty using chance constraint programming to minimize total cost and meeting customers' demands. Vincent et al (2010b) used a heuristic algorithm to determine optimal decisions in an FLRP under capacity considerations. Zarandi et al (2011b) presented a fuzzy capacitated FLRP that includes location-allocation and routing decisions to locate depots among a set of candidate nodes. Notably, a time window is taken into account to ensure customer satisfaction in this study. Küçükdeniz et al (2012b) proposed a fuzzy FLAP under uncertainty using convex optimization. In this study, a combination of clustering and fuzzy programming is utilized to solve the problem. Contardo et al (2013) proposed an FLRP that is solved using an exact cut-and-column algorithm. Nadizadeh & Nasab (2014b) presented an FLRP under uncertainty using a fuzzy programming approach that is solved using heuristic algorithms. In this study, the transportation vehicles and other facilities are under capacity considerations and the supply chain (SC) aims to meet customer's demands with the lowest risk. (Rahmani & MirHassani, 2014b) proposed a facility location problem that aimed to take optimal strategic and operational decisions to satisfy customer's demands along with minimizing the total system cost. The presented model is solved using heuristic algorithms. Khalili et al (2015) applied an extended queue theory-based model to locate warehouses with capacity considerations in a fuzzy environment optimally, and the study mainly aims to minimize the total cost. Diabat (2016b) discussed a location inventory problem with exclusive sourcing strategies taking into account capacity considerations. Nadizadeh & Kafash (2019b) presented an FLRP in a fuzzy environment with concurrent specified demands. This study aims to minimize the total distribution costs, including routing, opening, and employing of facilities. Khatami Firouzabadi et al (2019b) proposed a hybrid model to make tactical decisions in a glassware manufacturing company. In this study also some MADM techniques are applied.

The model efforts in the area of SCND under disruption and operational risks have mostly focus on different strategies to weaken the destructive impacts of various threats on the SC. Supply chain management (SCM) must take precautionary measures such as storing products and holding safety stock, multiple sourcing, providing backup facilities to cope with disruption risk, which are considered as SC resilience strategies. Silva & De la Figuera (2007b) discussed SCND using backlogging probabilities. In this study, also queue theory is applied, and the customer's demands considered as a parameter with inherent risk. The problem was solved using an adaptive metaheuristic algorithm. (Garcia-Herreros et al, 2014) proposed a resilient SC taking into account facilities with disruption risks. the developed model has based on DCs with complete and partial disruption, which are modeled using a two-stage stochastic programming approach. (Fattahi et al, 2017) designed a resilient and responsive SC under uncertainty and disruption, considering customers with high sensitivity to delivery time. They proposed a MILP model that customers demand depends on their adopter facilities and the lead times. (Ghavamifar et al, 2018) presented a competitive and resilient SC under disruption risks. In the proposed model, a Bi-Level Multi-Objective Programming (MOP) approach is applied to design a competitive SC. (Diabat et al, 2019) developed a perishable product SCND taking into account facilities' reliability and disruption risks. They utilized robust optimization and multi-criteria decision making (MCDM) to design a resilient supply chain under disruption considerations. (Zahiri et al, 2017) presented a pharmaceutical SCND under uncertainty and disruption considerations applying environmental and social concerns. They utilized a robust hybrid approach to cope with the operational risks within the specified framework.

A more detailed classification of the literature on distribution network design is illustrated in Table 1 by considering six characteristics, including type of facilities, number and type of objective functions, sourcing methodology, modeling considerations, and solution approach. Table 1 demonstrates some results as follows. Most facility location problems were costly optimized, and little attention has been paid to other objectives, including minimum total distance, etc. In the reviewed articles, the type of sourcing was often considered single; the mathematical model was mostly formulated in a deterministic space. Finally, the approach adopted to solve the problem is often metaheuristic.

Table 1. Overview of literature on distribution network design under risk

Reference	Facility		Objective		Objective type				Sourcing		Modeling		Solution approach			
					Cost			Other								
	Single	Multi	Single	Multi	Holding	Opening	Transportation	Distance traveled	Single	Multiple	Deterministic	Stochastic	Exact	Metaheuristic	simulation	Hybrid
(Klose & Drexl, 2005a)		✓	✓		✓		✓		✓		✓		✓			
(Silva & De la Figuera, 2007a)		✓	✓			✓	✓			✓		✓		✓	✓	✓
(Barreto et al, 2007a)		✓	✓					✓	✓		✓			✓		
(Prins et al, 2007a)	✓		✓					✓	✓		✓			✓		✓
(Chen & Ting, 2008)		✓	✓			✓	✓		✓		✓			✓		
(Lin, 2009a)		✓	✓		✓	✓	✓		✓			✓		✓		
(Jafari et al, 2010a)		✓		✓		✓	✓	✓		✓		✓				✓
(Vincent et al, 2010a)		✓	✓		✓	✓	✓		✓		✓			✓	✓	
Fazel (Zarandi et al, 2011a)		✓	✓					✓		✓		✓			✓	✓
(Küçükdeniz et al, 2012a)		✓	✓			✓	✓			✓	✓			✓		✓
(Contardo et al, 2014)		✓	✓			✓			✓		✓		✓			
(Nadizadeh & Nasab, 2014a)		✓		✓		✓	✓	✓		✓		✓		✓		✓
(Rahmani & MirHassani, 2014a)		✓	✓			✓	✓	✓		✓				✓		✓
(Diabat, 2016a)		✓	✓			✓	✓		✓		✓		✓			
(Khalili & Lotfi, 2015)		✓		✓		✓				✓		✓	✓			
(Nadizadeh & Kafash, 2019a)		✓	✓			✓	✓		✓				✓	✓	✓	
(Khatami Firouzabadi et al, 2019a)			✓	✓		✓	✓	✓	✓		✓		✓			
This paper		*		*	*	*	*	*		*		*	*		*	

The proposed research is a Multi-Objective, Stochastic, multiplicative, capacitated, and multiple sourcing FLAP that is solved using an exact methodology. This study takes into account minimizing distribution system costs, total distances traveled by transportation facilities, and establishing social justice in the distribution of end products. In the mathematical model, shortages are calculated in all echelons of the distribution system. We also seek to minimize the maximum shortages occurring in different customer zones to establish social justice in the distribution system. Considering the significant influence of uncertainty and disruption risks on the different facilities, routes among them, product demand, and other parameters, attempts have been made to cope with the operational and disruption risks in the presented framework by developing a two-stage robust possibilistic approach.

The research gaps are extracted as follows. First, the design of a multi-period distribution network, including warehouses, depots, and distribution centers have not been widely discussed in the literature. Second, only a few studies consider disruption in facilities and roots between them simultaneously. Third, only some recent studies take into account disruption and operational risks at the same time. Fourth, most of the available studies do not investigate social justice or social impact in the distribution of products in customer zones. Sixth, only a few studies discussed designing a resilient distribution network that can cope with disruptions at the least cost and damage.

Given the above-mentioned gaps, this paper extends the study area by presenting a novel multi-period, multi-product distribution network design problem, which is a Multi-Objective model to optimize the total distribution network cost, the total environmental impact and maximum lost sale in customer zones. This study takes into account disruption and operational risks by applying a two-stage stochastic programming approach and a robust possibilistic optimization simultaneously. In this study, it is assumed that if a facility or a rout is disrupted, it won't be accessible and cannot be recovered. The model decisions include locating central warehouses and urban depots as well as determining the amount of product shipped between facilities, the amount of inventory that should be kept in some facilities, and finally, the number of lost sales for different products in each market zones.

2-1- Major contributions in the proposed model

Based on the reviewed papers, we apply some significant contributions to this study. Table 2 illustrates the main contributions considered in the proposed model. First, we take into account simultaneous disruption in facilities, including suppliers cluster, central warehouses, urban depots, distribution centers, customer zones, and routes among them (multiple disruptions). The mentioned contributions are applied in constraint (10-13). It should be noted that the impact of disruption risk on the capacities of each facility is considered with a complete disruption approach, which means a disrupted facility will be Inaccessible. These contributions are considered in constraint (16-25). We also tried to establish social justice in distribution through minimizing the expected maximum lost sale based on disruption scenarios between customer zones, which is applied in term (6). The next contribution enforces coping with the uncertainty using a hybrid two-stage robust possibilistic programming, which is wholly discussed in section 4-1.

Table 2. Major contributions of this study

Contribution	The intended purpose
Considering thedisruption in facilities and routes among them simultaneously (multiple disruptions)	Providing supply chain preparedness to counter disruption risk
Considering complete disruption in different facilities	Taking into account the consequences of supply chain disruption risk
Suggesting Minimizing the maximum lost sales at customer zones as a new objective function	The establishment of social justice in product distribution between different customer zones
Coping with uncertainty by applying a hybrid two-stage robust possibilistic programming	Preventing problem infeasibility and taking into account all possible scenarios for the costs of establishment and variable costs.

3-Problem statement and mathematical formulation

In this section, we first present the problem description and related assumptions. Next, the problem is formulated using a mixed-integer linear programming (MILP) approach.

The problem studied in this paper is based on a real-world case. We examine the network design of a forward distribution system that is multi-product, multi-level, multi-period, and multi-stage that is vulnerable to operational and disruption risk. As illustrated in figure 1, the distribution system under investigation consists of different customer zones (CZs), distribution centers (DCs), urban depots (UDs), central warehouses (CWs), and a supplier cluster. The distribution network entails forward flows of products. In the flow of items, central warehouses receive parts from supplier clusters to pack the products and serve urban depots. Authorized products will be shipped from urban depots to the applicant distribution centers. Finally, distribution centers will serve customer zones.

It is assumed that suppliers, central warehouses, urban depots, distribution centers are vulnerable to operational and disruption risks. In other words, disruption risk can completely or partially affect all parameters related to different distribution facilities. To reduce the effects of operational risks, we applied a hybrid robust possibilistic programming model to minimize the total distribution system cost, comprising costs for lost sales, inventory, transportation, and facility establishment. We also aim to minimize the total environmental impact, and the maximum lost sales occur in customer zones. Here, a two-stage stochastic programming model is utilized to mitigate disruption risks on the route to facilities and in them. The first stage determines the strategic decisions related to the opening of CWs and UDs. The second stage involves determining operational decisions, including allocating CWs to UDs, UDs to DCs, and finally, DCs to CZs. It also includes assessing the number of products transmitted among different nodes of the distribution chain, the inventory amount that should be held in CWs, UDs and DCs considering disruption in facilities and routes. The disruption scenarios investigated in this study are such that if a route or a facility is disrupted, then it would no longer be accessible.

Figure 1 indicates the investigated multi-level distribution system. In the structure of the above-mentioned distribution system, several routes are taken into account between facilities. Notably, only a single route can be selected among the available routes.

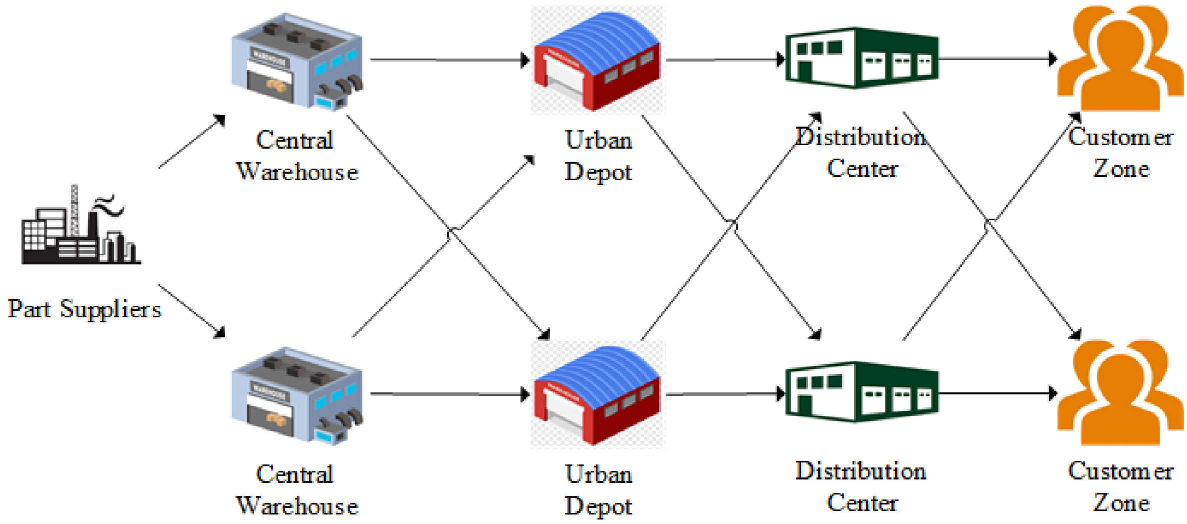

Fig 1. Conceptual model of the distribution system

The conceptual questions raised in this study are as follows, which should be answered in the section of results:

- Are distributed products classified independently or considered as family products in the problem?
- How to allocate distribution centers to urban depots to satisfy customer demand?
- Are the selected candidate locations suitable for the establishment of new central warehouses and urban depots?
- Should the problem be investigated in the space of certainty or uncertainty?
- Is there a need to create new central warehouses?

The presented framework determines some strategic and operational decisions as follows:

- Determining number and location of central warehouses and urban depots that can be established among a set of potential locations
- Allocation of customer zones to distribution centers, distribution centers to the urban depots, urban depots to central warehouses to meet customers' demands
- Determining amounts of transmission between facilities, quantities of inventories and lost sales
- Reducing the cost of opening facilities, holding, transportation, and lost sales
- Establishing justice in supplying parts needed by different customer zones
- Considering the minimum distance traveled between facilities

The following further assumptions regarding the problem formulation should be taken into account:

- Locations are in discrete space.
- Only a single route between facilities can be chosen.

- Facilities are capacitated in the distribution system to provide service.
- The supply and production capacity of the facilities are different
- In each district, a maximum of one distribution center can exist.
- By increasing cargo volume, transfer costs will increase.
- The cost of opening facilities, the location of the supplier cluster, and customers are known.
- The shortage is allowed in customer zones that are considered as lost sales.
- The customer has the possibility of early delivery of the product, which is subject to holding products.
- The input of the model is known. Therefore, the model is definite and static.

Given the fact that suppliers are obliged to send all of the parts to the central warehouses in the concerned distribution network, so there is no need to define the index of the supplier, and only the total flow of parts shipped from all suppliers to a central warehouse is defined.

3-1- Model formulation

The following sets, parameters, and decision variables are employed to formulate the proposed distribution network design under operational risks and disruption considerations. It should be noted that the beneficiaries of this research are two companies, IKCO and ISACO. Consequently, the model formulation of this research is carried out from their perspective.

3-1-1- Sets and Indices

I	Set of potential locations for central warehouses indexed by i	$i \in I$
J	Set of potential locations for urban depots indexed by j	$j \in J$
K	Set of different types of product indexed by k	$k \in K$
L	Set of authorized distribution centers indexed by l	$l \in L$
M	Set of indexed customer zones indexed by m	$m \in M$
R	Set of routes indexed by r	$r \in R$
S	Set of disruption scenarios indexed by s	$s \in S$
T	Set of time periods indexed by t	$t \in T$

3-1-2-Parameters

Technical parameters

$LD^{\max}$	Maximum number of urban depots that can be established
$CW^{\max}$	Maximum number of openable central warehouses that can be established
HCD_{jt}^{s}	Holding capacity of urban depot j in period t under scenario s (m^3)
HCE_{lt}^{s}	Holding capacity of distribution centers l in period t under scenario s (m^3)
HCW_{it}^{s}	Holding capacity of central warehouse i in period t under scenario s (m^3)
SCS_{kt}^{s}	Shipping capacity of product k at supplier cluster in period t under scenario s (ton)
SCW_{kit}^{s}	Shipping capacity of product k at central warehouse i in period t under scenario s (ton)
SCD_{kjt}^{s}	Shipping capacity of product k at urban depot j in period t under scenario s (ton)
SCE_{klt}^{s}	Shipping capacity of product k at distribution center l in period t under scenario s (ton)
ACW_{kit}^{s}	Receive capacity of product k at central warehouse i in period t under scenario s (ton)
ACD_{kjt}^{s}	Receive capacity of product k at urban depot j in period t under scenario s (ton)

ACE^{s}_{klt}	Receive capacity of product k at distribution center l in period t under scenario s (ton)
DEC^{s}_{kmt}	Demand of product k at customer zone m in period t under scenario s (ton)
V_k	The volume occupied by a product k (m^3/ton)
d_{ijr}	Distance between central warehouse i and urban depot j by route r (Km)
d_{jlr}	Distance between urban depot j and distribution center l by route r (Km)
d_{lmr}	Distance between distribution center l and customer zone m by route r (Km)
θ^{s}_{t}	A binary parameter, equal to 1 if supplier cluster is disrupted in period t under scenario s; 0, otherwise.
χ^{s}_{it}	A binary parameter, equal to 1 if central warehouse i is disrupted in period t under scenario s; 0, otherwise.
λ^{s}_{jt}	A binary parameter, equal to 1 if urban depot j is disrupted in period t under scenario s; 0, otherwise.
ω^{s}_{lt}	A binary parameter, equal to 1 if distribution center l is disrupted in period t under scenario s; 0, otherwise.
η^{s}_{irt}	A binary parameter, equal to 1 if route r between supplier cluster and central warehouse i is disrupted in period t under scenario s; 0, otherwise.
κ^{s}_{ijrt}	A binary parameter, equal to 1 if route r between central warehouse i and urban depot j is disrupted in period t under scenario s; 0, otherwise.
φ^{s}_{jlrt}	A binary parameter, equal to 1 if route r between urban depot j and distribution center l is disrupted in period t under scenario s; 0, otherwise.
ψ^{s}_{lmrt}	A binary parameter, equal to 1 if route r between distribution center l and customer zone m is disrupted in period t under scenario s; 0, otherwise.

Economic parameters

FOD_j	Fixed cost of opening urban depot j (million rials)
FOW_i	Fixed cost of opening central warehouse m (million rials)
HOD^{s}_{kjt}	Unit cost of holding product k at urban depot j in period t under scenario s (million rials / ton)
HOE^{s}_{klt}	Unit cost of holding product k at distribution center l in period t under scenario s (million rials / ton)
HOW^{s}_{kit}	Unit cost of holding product k at central warehouse i in period t under scenario s(million rial / ton)
TWD^{s}_{kijrt}	Unit transportation cost of product k from central warehouse i to urban depot j by route r in period t under scenario s (million rials / ton.km)
TDE^{s}_{kjlrt}	Unit transportation cost of product k from urban depot j to distribution center l by route r in period t under scenario s (million rials / ton.km)
TEC^{s}_{klmrt}	Unit transportation cost of product k from distribution center l to customer zone m by route r in period t under scenario s (million rials / ton.km)
TSW^{s}_{kirt}	Unit transportation cost of product k from supplier cluster to central warehouse i by route r in period t under scenario s (million rials / ton.km)
$SHCE^{s}_{kmt}$	Unit cost of lost sales for product k at customer zone m in period t under scenario s (million rials / ton)

Environmental parameters

EOD_j	Unit environmental impact associated with establishing urban depot j (amount / ton)
EOW_i	Unit environmental impact associated with establishing central warehouse i (amount / ton)
EHW^{s}_{kit}	Unit environmental impact of holding product k at central warehouse i in period t under scenario s (amount / ton)

EHD_{kjt}^{s}	Unit environmental impact of holding product k at urban depot j in period t under scenario s (amount / ton)
EHE_{klt}^{s}	Unit environmental impact of holding product k at distribution center l in period t under scenario s (amount / ton)
$ETWD_{kijrt}^{s}$	Unit environmental impact of shipping product k from central warehouse i to urban depot j by route r in period t under scenario s (million rial / ton.km)
$ETDE_{kjlrt}^{s}$	Unit environmental impact of shipping product k from urban depot j to distribution center l by route r in period t under scenario s (million rial / ton.km)
$ETEC_{klmrt}^{s}$	Unit environmental impact of shipping product k from distribution center l to customer zone m by route r in period t under scenario s (million rial / ton.km)
$ETSW_{kirt}^{s}$	Unit environmental impact of shipping product k from supplier cluster to central warehouse i by route r in period t under scenario s (million rial / ton.km)

3-1-3- Decision variables

FEC_{klmrt}^{s}	Quantity of product k shipped from distribution center l to customer zone m by route r in period t under scenario s (ton)
FWD_{kijrt}^{s}	Quantity of product k shipped from central warehouse i to urban depot j by route r in period t under scenario s (ton)
FDE_{kjlrt}^{s}	Quantity of product k shipped from urban depot j to distribution center l by route r in period t under scenario s (ton)
FSW_{kirt}^{s}	Quantity of product k shipped from supplier to central warehouse i by route r in period t under scenario s (ton)
IW_{kit}^{s}	Inventory of product k at central warehouse i in period t under scenario s (ton)
ID_{kjt}^{s}	Inventory of product k at urban depot j in period t under scenario s (ton)
IE_{klt}^{s}	Inventory of product k at distribution center l in period t under scenario s (ton)
SLC_{kmt}^{s}	Lost sale of product k at customer zone m in period t under scenario s (ton)
OD_{j}	A binary variable equal to 1 if urban depot j is established; 0, otherwise.
OW_{i}	A binary variable equal to 1 if central warehouse i is established; 0, otherwise.
WD_{ijrt}^{s}	A binary variable equal to 1 if urban depot j is allocated to central warehouse i by route r in period t under scenario s; 0, otherwise.
DE_{jlrt}^{s}	A binary variable equal to 1 if distribution center l is allocated to urban depot j by route r in period t under scenario s; 0, otherwise.
EC_{lmrt}^{s}	A binary variable equal to 1 if customer zone m is allocated to distribution center l by route r in period t under scenario s; 0, otherwise.

After applying the two-stage modeling procedure (Sabet et al, 2019) to our problem, the mathematical model is then as follows:

3-1-4- Objective functions

Total cost

The objective function (1) guarantees the minimization of the total distribution costs, including transportation, establishment, holding, and shortage costs.

$$
\begin{aligned}
Min\ TC =& \sum_{j\in J} FOD_j OD_j + \sum_{i\in I} FOW_i OW_i + \sum_{s\in S}\pi_s \Big(\sum_{k\in K}\sum_{j\in J}\sum_{t\in T} HOD^s_{kjt} ID^s_{kjt} + \sum_{k\in K}\sum_{l\in L}\sum_{t\in T} HOE^s_{klt} IE^s_{klt} \\
&+ \sum_{k\in K}\sum_{i\in I}\sum_{t\in T} HOW^s_{kit} IW^s_{kit} + \sum_{k\in K}\sum_{i\in I}\sum_{r\in R}\sum_{t\in T} TSW^s_{kirt} FSW^s_{kirt} + \sum_{k\in K}\sum_{i\in I}\sum_{j\in J}\sum_{r\in R}\sum_{t\in T} TWD^s_{kijrt} FWD^s_{kijrt} d_{ijr} \\
&+ \sum_{k\in K}\sum_{l\in L}\sum_{m\in M}\sum_{r\in R}\sum_{t\in T} TEC^s_{klmrt} FEC^s_{klmrt} d_{lmr} + \sum_{k\in K}\sum_{j\in J}\sum_{l\in L}\sum_{r\in R}\sum_{t\in T} TDE^s_{kjlrt} FDE^s_{kjlrt} d_{jlr} \\
&+ \sum_{k\in K}\sum_{m\in M}\sum_{t\in T} SHCE^s_{kmt} SLC^s_{kmt}\Big)
\end{aligned}
\tag{1}
$$

Total environmental impact

The total environmental impact, including transportation (TTE_s), establishment (TOE), and holding (THE_s) impacts are defined as the second objective function by terms (2-5).

$$
Min TEI = TOE + \sum_{s\in S} \pi_S \left(TTE_S + THE_S\right) \tag{2}
$$

$$
\begin{aligned}
TTE_o =& \sum_{k\in K}\sum_{i\in I}\sum_{r\in R}\sum_{t\in T} ETSW^s_{kirt} FSW^s_{kirt} + \sum_{k\in K}\sum_{i\in I}\sum_{j\in J}\sum_{r\in R}\sum_{t\in T} ETWD^s_{kijrt} FWD^s_{kijrt} d_{ij} \\
&+ \sum_{k\in K}\sum_{l\in L}\sum_{m\in M}\sum_{r\in R}\sum_{t\in T} ETEC^s_{klmrt} FEC^s_{klmrt} d_{lm} + \sum_{k\in K}\sum_{j\in J}\sum_{l\in L}\sum_{r\in R}\sum_{t\in T} ETDE^s_{kjlrt} FDE^s_{kjlrt} d_{jl}
\end{aligned}
\tag{3}
$$

$$
THEo = \sum_{k\in K}\sum_{j\in J}\sum_{t\in T} EHOD^s_{kjt} ID^s_{kjt} + \sum_{k\in K}\sum_{l\in L}\sum_{t\in T} EHOE^s_{klt} IE^s_{klt} + \sum_{k\in K}\sum_{i\in I}\sum_{t\in T} EHOW^s_{kit} IW^s_{kit} \tag{4}
$$

$$
TOE = \sum_{j\in J} EOD_j OD_j + \sum_{i\in I} EOW_i OW_i \tag{5}
$$

Establishing social justice

One of the most essential considerations in distribution network design is to ensure fairness in the distribution of products to customer zones. To aim this, we tried to minimize the expected maximum lost sale based on disruption scenarios between customer zones and establish social justice through the non-linear term (6). This objective function is a nonlinear term, and it should be linearized to reduce problem complexity.

$$
\underset{m}{MinMax} \sum_{k\in K}\sum_{s\in S}\sum_{t\in T} \pi_S SLC^s_{kmt} \tag{6}
$$

3-1-5- Constraints

$$
\sum_{r\in R} DE^s_{jlrt} \le 1 \qquad \forall l\in L, \forall s\in S \tag{7}
$$

$$
\sum_{r\in R} WD^s_{ijrt} \le 1 \qquad \forall j\in J, \forall s\in S \tag{8}
$$

$$
\sum_{r\in R} EC^s_{lmrt} \le 1 \qquad \forall m\in M, \forall s\in S \tag{9}
$$

$$
DE^s_{jlrt} \le OD_j\left(1-\lambda^s_{jt}\right)\left(1-\omega^s_{lt}\right)\left(1-\varphi^s_{jlrt}\right) \qquad \forall j\in J, \forall l\in L, \forall s\in S \tag{10}
$$

$$WD_{ijrt}^{s} \le OW_i\left(1-\chi_{it}^{s}\right)\left(1-\lambda_{jt}^{s}\right)\left(1-\kappa_{ijrt}^{s}\right) \qquad \forall i \in I, \forall j \in J, \forall s \in S \qquad (11)$$

$$WD_{ijrt}^{s} \le OD_j\left(1-\chi_{it}^{s}\right)\left(1-\lambda_{jt}^{s}\right)\left(1-\kappa_{ijrt}^{s}\right) \qquad \forall i \in I, \forall j \in J, \forall s \in S \qquad (12)$$

$$EC_{lmrt}^{s} \le \left(1-\omega_{lt}^{s}\right)\left(1-\psi_{lmrt}^{s}\right) \qquad \forall i \in I, \forall j \in J, \forall s \in S \qquad (13)$$

$$\sum_{j \in J} OD_j \le LD^{\max} \qquad (14)$$

$$\sum_{i \in I} OW_i \le CW^{\max} \qquad (15)$$

$$\sum_{i \in I}\sum_{r \in R} FSW_{kirt}^{s} \le SCS_{kt}\left(1-\theta_t^{s}\right) \qquad \forall k \in K, \forall t \in T, \forall s \in S \qquad (16)$$

$$\sum_{j \in J}\sum_{r \in R} FWD_{kijrt}^{s} \le SCW_{kit}\left(1-\chi_{it}^{s}\right)OW_i \qquad \forall\ k \in K\ , i \in I,\ t \in T, \forall s \in S \qquad (17)$$

$$\sum_{l \in L}\sum_{r \in R} FDE_{kjlrt}^{s} \le SCD_{kjt}\left(1-\lambda_{jt}^{s}\right)OD_j \qquad \forall k \in K, \forall j \in J, \forall t \in T, \forall s \in S \qquad (18)$$

$$\sum_{m \in M}\sum_{r \in R} FEC_{klmrt}^{s} \le SCE_{klt}\left(1-\omega_{lt}^{s}\right) \qquad \forall k \in K, \forall l \in L, \forall t \in T, \forall s \in S \qquad (19)$$

$$\sum_{r \in R} FSW_{kirt}^{s} \le ACW_{kit}\left(1-\chi_{it}^{s}\right)OW_i \qquad \forall\ k \in K\ , i \in I,\ t \in T, \forall s \in S \qquad (20)$$

$$\sum_{i \in I}\sum_{r \in R} FWD_{kijrt}^{s} \le ACD_{kjt}\left(1-\lambda_{jt}^{s}\right)OD_j \qquad \forall k \in K, \forall j \in J, \forall t \in T, \forall s \in S \qquad (21)$$

$$\sum_{l \in L}\sum_{r \in R} FDE_{kjlrt}^{s} \le ACE_{klt}\left(1-\omega_{lt}^{s}\right) \qquad \forall k \in K, \forall l \in L, \forall t \in T, \forall s \in S \qquad (22)$$

$$\sum_{k \in K} V_k\, ID_{kjt}^{s} \le HCD_{jt}\left(1-\lambda_{jt}^{s}\right)OD_j \qquad \forall j \in J, \forall t \in T, \forall s \in S \qquad (23)$$

$$\sum_{k \in K} V_k\, IW_{kit}^{s} \le HCW_{it}\left(1-\chi_{it}^{s}\right)OW_i \qquad \forall i \in I, \forall t \in T, \forall s \in S \qquad (24)$$

$$\sum_{k\in K} V_k\, IE^s_{klt} \;\le\; HCE_{lt}\left(1-\omega^s_{lt}\right) \qquad \forall l\in L, \forall t\in T, \forall s\in S \qquad (25)$$

$$\sum_{k\in K}\sum_{r\in R}\sum_{t\in T} FDE^s_{kjlrt} \;\le BM\; DE^s_{jl} \qquad j\in J, \forall\, l\in L, \forall s\in S \qquad (26)$$

$$\sum_{k\in K}\sum_{r\in R}\sum_{t\in T} FWD^s_{kijrt} \;\le BM\; WD^s_{ij} \qquad i\in I, \forall\; j\in J, \forall s\in S \qquad (27)$$

$$\sum_{k\in K}\sum_{r\in R}\sum_{t\in T}\sum_{s\in S} FSW^s_{kirt} \;\le BM\; OW_i \qquad \forall i\in I \qquad (28)$$

$$\sum_{k\in K}\sum_{r\in R}\sum_{t\in T} FEC^s_{klmrt} \;\le BM\; EC^s_{lm} \qquad \forall l\in L, \forall m\in M, \forall s\in S \qquad (29)$$

$$\sum_{k\in K}\sum_{r\in R}\sum_{t\in T} FWD^s_{kijrt} \le BM\; WD^s_{ij} \qquad \forall i\in I, \forall j\in J, \forall s\in S \qquad (30)$$

$$\sum_{k\in K}\sum_{r\in R}\sum_{t\in T} FDE^s_{kjlrt} \le BM\;\; DE^s_{jl} \qquad \forall j\in J, \forall l\in L, \forall s\in S \qquad (31)$$

$$\sum_{l\in L}\sum_{r\in R} FEC^s_{klmrt} + SLC^s_{kmt} = DEC^s_{kmt} \qquad \forall k\in K, \forall\, m\in M, t\in T, \forall s\in S \qquad (32)$$

$$IE^s_{klt} = IE^s_{klt-1} + \sum_{j\in J}\sum_{r\in R} FDE^s_{kjlrt} - \sum_{m\in M}\sum_{r\in R} FEC^s_{klmrt} \qquad \forall\, k\in K, \forall l\in L,\;\; \forall t\in T, \forall s\in S \qquad (33)$$

$$ID^s_{kjt} = ID^s_{kjt-1} + \sum_{i\in I}\sum_{r\in R} FWD^s_{kijrt} - \sum_{l\in L}\sum_{r\in R} FDE^s_{kjlrt} \qquad \forall k\in K, \forall j\in J,\;\; t\in T, \forall s\in S \qquad (34)$$

$$IW^s_{kit} = IW^s_{kit-1} + \sum_{r\in R} FSW^s_{kirt} - \sum_{j\in J}\sum_{r\in R} FWD^s_{kijrt} \qquad k\in K, \forall\, i\in I, ,\; t\in T, \forall s\in S \qquad (35)$$

$$FEC^S_{klmrt}, FWD^S_{kijrt}, FDE^S_{kjlrt}, FSW^S_{kirt}, IW^S_{kit}, ID^S_{kjt}, IE^S_{klt}, SLC^S_{kmt} \;\ge 0 \qquad \forall\, i\in I, \forall j\in J, \forall\, k\in K, \forall l\in L, \forall m\in M, \forall s\in S\;, \forall t\in T \qquad (36)$$

$$OD_j, OW_i, WD^S_{ijrt}, DE^S_{jlrt}, EC^S_{lmrt} \in \{0,1\} \qquad \forall\, i\in I, \forall j\in J, \forall l\in L, \forall m\in M, \forall r\in R, \forall s\in S, \forall t\in T \qquad (37)$$

Constraints (7-9) ensure that between supplier cluster and each central warehouse, each central warehouse and urban depot and finally each urban depot and distribution center, one root is allocated. Constraint (10) enforces that if an existing distribution center is allocated to an opened urban depot, facilities and routes between them are not disrupted. Constraints (11-13) state the same condition as the constraint (10) between echelons supplier cluster and central warehouse, central warehouse and urban depot, distribution center, and customer zone. Constraints (14-15) stipulate the maximum number of urban depots and central warehouses that can be established. Constraints (16-19) provide that the transportation amounts must not exceed the shipping or supply capacity of supplier cluster, central warehouses, urban depots, and distribution centers considering complete disruption risk in facilities. Constraints (20-22) stipulate that the number of products that are shipped to a facility must not exceed the receiving capacity of that facility considering complete disruption risk in facilities. Constraints (23-25) provide that Inventory amounts kept by a facility must not exceed the holding capacity of that facility considering complete disruption risk in facilities. Constraints (26-31) guarantee that products cannot be shipped from a facility to another facility to which it is not assigned. Constraint (32) provides demand satisfaction for customer zones. Constraints (33-35) are inventory balance equations for central warehouses, urban depots, and distribution centers. Constraints (36-37) provide binary and non-negativity restrictions on the decision variables.

4- Solution approach

The optimization model proposed in the previous section is entangled with a series of the problems, including (1) the third objective function is taken into account a non-linear term and should be converted into a linear form, (2) Some parameters in the proposed model are affected by uncertainty, for which an appropriate method is needed to be employed to cope with such operational risks, (3) the proposed model encompasses two objective functions. Accordingly, we should exploit a Multi-Objective programming (MOP) method to solve the model.

The following actions took place to tackle the above-mentioned problems:

- The maxi-min objective function as a non-linear term has been converted into a linear form by applying an appropriate procedure
- A two-stage robust possibilistic programming model is utilized to capture the operational risks
- To convert the proposed Multi-Objective model into single-objective one, ε-constraint method is deployed.

4-1- linearization approach

As mentioned before, the objective function (3) is considered as a non-linear term that destroys the linearity condition of the proposed model. The nonlinear term can be converted into the linear one by applying the constraints (38-39) as follows:

$$Min \;\; SV \tag{38}$$

$$\sum_{k \in K} \sum_{s \in S} \sum_{t \in T} \pi_s \, SLC_{kmt}^{s} \leq SV \qquad \forall m \in M \tag{39}$$

4-2- The implementation of MOP

4-2-1- ε-constraint method

MOP enables Multi-Objective problems to be optimized over a feasible region. Different approaches are proposed to transform a Multi-Objective problem into single-objective such as no-preference methods, priori methods, posteriori methods, interactive methods, etc. In this study, the ε-constraint method is employed to convert the Multi-Objective model into a single objective formulation.

An exclusive benefit of applying the ε-constraint method in Multi-Objective problems is that by restraining efficient solutions, Pareto frontier can be easily obtained. ε-constraint is a powerful method with tangible success in MOP, notably in SCND problems (Olivares-Benitez et al, 2013). In multi-objective problems, objectives are either minimization or maximization. Solving multi-objective problems using ε constraint includes a methodology as follows: First, we must determine the objective

function with the highest priority and consider it as the main objective, and then we must define the acceptable ε bounds for the remaining objectives. In fact, in the ε-constraint method, one objective function is optimized while ε bounds restrict the other objective functions. Consequently, we will define a new single objective problem (Dehghani et al, 2018a). Lower ε bounds are considered for the objective functions of maximizing, and upper ε bounds are provided for the minimization objective functions. we apply mathematical expressions as follows:
Suppose that a Multi-Objective problem is generally defined as follows:

$$\begin{aligned} &Min\ \ f_1, ..., f_k, ... , f_{j-1} \\ &Max\ \ f_j, ..., f_n \\ &S.t: \quad X \in \Omega \end{aligned} \tag{40}$$

Ω represents the feasible region that can be defined by equality and, or inequality constraints. If the objective function f_k is identified as the highest priority objective in Multi-Objective problem and the vector ε is defined as ε bounds for other objective functions. The Multi-Objective problem is solved using the ε-constraint method as follows:

$$\begin{aligned} &Min\ \ f_k \\ &f_1 \le \varepsilon_1 \quad ,..., \ f_{k-1} \le \varepsilon_{k-1} \\ &f_{k+1} \le \varepsilon_{k+1}\ ,...., \ f_{j-1} \le \varepsilon_{j-1} \\ &f_j \ge \varepsilon_j\ ,....., \quad f_n \ge \varepsilon_n \\ &X \in \Omega \end{aligned} \tag{41}$$

Where the vector of upper and lower ε bounds, $\varepsilon = (\varepsilon_1, \varepsilon_2, ..., \varepsilon_n)$, Specifies the upper limit for minimization objective functions and the lower limit for objective functions of maximizing. It should be noted that by altering the epsilon bound vector along the Pareto frontier and making a new optimization problem for each new vector, the Pareto optimal set can be achieved.

Determining upper and lower ε bounds

At each iteration of the ε-constraint method, lower and upper ε bounds are determined as follows. Suppose that objective function f_k has the highest priority for the decision-maker. First, we solve a single objective problem based on f_k as objective function and technical constraints as follows:

$$\begin{aligned} &Min\ \ f_k \\ &X \in \Omega \end{aligned} \tag{42}$$

Consider vector X^* as an optimal solution for the above-mentioned problem, so Z^{nadir} will be obtained for both objectives of maximizing and minimizing as follows:

$$Z_i^{Nadir} = f_i(X^*) \qquad \forall i = 1,2,...,k-1,k+1,...,n \tag{43}$$

After that, we will optimize objective functions independently except f_k to determine the optimal objective functions vector Z^* as follows:

$$Z_i^* = f_i^*(x) \qquad \forall i = 1,2,...,k-1,k+1,...,n \tag{44}$$

Upper ε bounds vector, $\varepsilon = (\varepsilon_1, \varepsilon_2, ..., \varepsilon_{k-1})$, indicates the maximum value that each objective of minimizing can have. Suppose that the problem is executed in n iterations, upper ε bounds are determined in each iteration r as follows:

$$\varepsilon_i = Z_i^* + \frac{r}{n}\left(Z_i^{nadir} - Z_i^*\right) \qquad \forall i = 1,2,...,k-1 \tag{45}$$

Lower ε bounds vector, $\varepsilon = (\varepsilon_{k+1}, \varepsilon_2, ..., \varepsilon_n)$, specifies the minimum value that each objective of maximizing can have. Suppose we have *n* iterations; lower ε bounds are determined in each iteration *r* as follows:

$$\varepsilon_i = Z_i^{nadir} + \frac{r}{n}\left(Z_i^* - Z_i^{nadir}\right) \qquad \forall i = k+1,...,n \tag{46}$$

As mentioned before, the Pareto optimal set can be achieved by altering the ε bounds vector along the Pareto frontier. It is noteworthy that the generation of points on the Pareto frontier is illustrated in the section of results.

4-3- Robust optimization method

In this section, we apply a robust optimization approach to extend the proposed deterministic model in a robust formulation. Robust optimization techniques are efficient approaches to cope with different operational risks, especially in situations of inappropriate historical data or lack of knowledge to estimate the probability distributions of uncertain parameters.

In this study, a robust possibilistic method is provided to cope with the uncertainty of variable costs, fixed opening costs, demands, capacities, and other parameters of distribution network design model that are faced to uncertainty. For this purpose, we used the research carried out in 2012 by Pishvae et.al the robust possibilistic applied in this study, was based on an optimistic approach, so the objective function was significantly increased, but instead, maximum lost sales of products at customer zones was decreased. It should be noted that robustness was applied throughout the constraints, but only the most critical objective function, or in other words, minimization of the total distribution system costs (Dehghani et al, 2018b; Pishvaee et al, 2012b; Zokaee et al, 2017).

To work more convenient, the deterministic distribution network design problem studied in this paper (excluding second and third objective function) can be compactly formulated as follows:

$$\begin{aligned} & Min \;\; Z = FY + CX \\ & S.t: \\ & A_1X \geq D_1 \qquad A_2X \geq D_2Y \\ & B_1X \leq S_1 \qquad B_2X \leq S_2Y \\ & C_1X \leq P_1 \qquad C_2X \leq P_2Y \\ & Y \in \{0,1\} \qquad X \geq 0 \end{aligned} \tag{47}$$

Where the vectors *F*, *C*, D_1, D_2, S_1, S_2, P_1, and P_2 indicate the fixed opening, variable transmission, holding and shortage costs, requirements for available facilities like distribution centers and customer zones, requirements for facilities that need opening, holding capacities for available facilities, holding capacities for facilities that require opening, shipping capacities for available facilities, shipping capacities for facilities that require opening, respectively. The matrices A_1, A_2, B_1, B_2, C_1, and C_2, are technical coefficient matrices of constraints. Additional vector *Y* and *X* define the binary opening variable and continuous inventory and flow variables, respectively. It should be noted that to apply the robust optimization to the proposed model, it is first necessary to convert the Multi-Objective problem to a single-objective problem using the ε-constraint method, then the robust optimization process can be executed.

Now consider vectors *F*, *C*, and technical coefficient matrices D_1, D_2, S_1, S_2, P_1, P_2 that represent the capacity and demand of facilities are the uncertain parameters in the formulation of the deterministic model. The expected value operator has been used to model the first objective function and the necessity measure to cope with chance constraints, including uncertain parameters that can be defined by triangular possibility distribution or triangular fuzzy number. Figure 2 illustrates that a membership function defines a triangular fuzzy number.

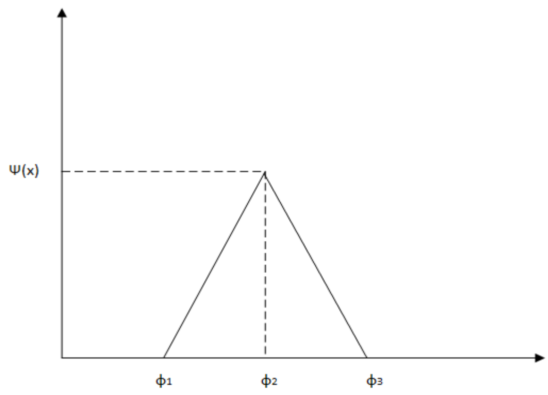

Fig 2. The triangular possibility distribution of fuzzy parameter ϕ

Based on the above-mentioned discussions, the FLAP chance constraint programming model can be stated for an optimistic formulation as follows:

$$\begin{aligned}
&Min\ \ Z = E\left[F\right]Y + E\left[C\right]X \\
&S.t: \\
&Pos\left\{A_1 X \ge D_1\right\} \ge \alpha \qquad Pos\left\{A_2 X \ge D_2 Y\right\} \ge \alpha \\
&Pos\left\{B_1 X \le S_1\right\} \ge \beta \qquad Pos\left\{B_2 X \le S_2 Y\right\} \ge \beta \\
&Pos\left\{C_1 X \le P_1\right\} \ge \beta \qquad Pos\left\{C_2 X \le P_2 Y\right\} \ge \beta \\
&Y \in \{0,1\} \qquad X \ge 0
\end{aligned} \tag{48}$$

The equivalent crisp model of the above formulation can be stated as follows:

$$\begin{aligned}
&Min\ E[Z] = \left(\frac{f_{(1)} + f_{(2)} + f_{(3)}}{3}\right)Y + \left(\frac{c_{(1)} + c_{(2)} + c_{(3)}}{3}\right)X \\
&S.t: \\
&A_1 x \ge \alpha D_1^{(1)} + (1-\alpha) D_1^{(2)} \qquad A_2 x \ge (\alpha D_2^{(1)} + (1-\alpha) D_2^{(2)})y \\
&B_1 X \le \beta S_1^{(3)} + (1-\beta) S_1^{(1)} \qquad B_2 X \le (\beta S_2^{(3)} + (1-\beta) S_2^{(1)})y \\
&C_1 X \le \beta P_1^{(3)} + (1-\beta) P_1^{(1)} \qquad C_2 X \le (\beta P_2^{(3)} + (1-\beta) P_2^{(1)})y \\
&Y \in \{0,1\} \qquad X \ge 0
\end{aligned} \tag{49}$$

In formulation (49), it is assumed that chance constraints should be satisfied with the confidence level that are parameters, and DM should determine these two parameters greater than 0.5, but determining confidence levels cause lowering mathematical accuracy.

Based on (Pishvaee et al, 2012a), the most accurate mathematical model for robust possibilistic FLAP can be formulated as follows:

$$\begin{aligned}
&Min\ E\left[Z\right] + \tau(Z_{\max} - Z_{\min}) + \eta_1\left[D_1^{(3)} - \alpha D_1^{(1)} - (1-\alpha) D_1^{(2)}\right] + \eta_2\left[D_2^{(3)} - \alpha D_2^{(1)} - (1-\alpha) D_2^{(2)}\right]Y \\
&+\omega_1\left[\beta S_1^{(3)} + (1-\beta) S_1^{(1)} - S_1^{(1)}\right] + \omega_2\left[\beta S_2^{(3)} + (1-\beta) S_2^{(1)} - S_2^{(1)}\right]Y + \gamma_1\left[\beta P_1^{(3)} + (1-\beta) P_1^{(1)} - P_1^{(1)}\right] \\
&+\gamma_2\left[\beta P_2^{(3)} + (1-\beta) P_2^{(1)} - P_2^{(1)}\right]Y \\
&S.t: \\
&A_1 x \ge \alpha D_1^{(1)} + (1-\alpha) D_1^{(2)} \qquad A_2 x \ge (\alpha D_2^{(1)} + (1-\alpha) D_2^{(2)})y \\
&B_1 X \le \beta S_1^{(3)} + (1-\beta) S_1^{(1)} \qquad B_2 X \le (\beta S_2^{(3)} + (1-\beta) S_2^{(1)})y \\
&C_1 X \le \beta P_1^{(3)} + (1-\beta) P_1^{(1)} \qquad C_2 X \le (\beta P_2^{(3)} + (1-\beta) P_2^{(1)})y \\
&Y \in \{0,1\}, \qquad X \ge 0, \qquad 0.5 < \alpha, \beta \le 1
\end{aligned} \tag{50}$$

In formulation (50), the first term in the objective function represents the expected value of z that results in the minimization of the expected total distribution system cost. The second term, $\tau(Z_{\max} - Z_{\min})$, illustrates the difference between the two extreme possible values of the objective function in which z_{max} and z_{min} can be defined as follows:

$$Z_{\max} = f_{(3)}y + c_{(3)}x$$
$$Z_{\min} = f_{(1)}y + c_{(1)}x \tag{51}$$

τ indicates the importance weight of this difference that is determined by DM. The third term, $\eta_1\left[D_1^{(2)} - \alpha D_1^{(1)} - (1-\alpha)D_1^{(2)}\right]$, considers the confidence level of each chance constraints in which η_1 is the unit penalty of the possible infeasibility of each constraint including an imprecise parameter (D_1) and the term $\left[D_1^{(2)} - \alpha D_1^{(1)} - (1-\alpha)D_1^{(2)}\right]$ indicates the difference between the worst-case value of an uncertain parameter and the value that is used in chance constraint programming. Other terms and parameters in objective function can be defined as the third term, but in some terms that are related to facilities that require opening, an opening variable *y* and Confidence level variables α or β are multiplied.

As it can be seen in the formulation (50), when parameters are assumed to be imprecise, the linearity of the chance constraints and the first objective function is destroyed in the proposed robust possibilistic programming model. The non-linear terms can be converted into the linear by defining some new auxiliary variables and adding several constraints to the primary model. To reduce the complexity of the non-linear problem and also easier to solve the model by exact algorithm, let w_1 and w_2 be auxiliary variables(vectors) that are defined as follows:

$$W_1 = \alpha.y$$
$$W_2 = \beta.y \tag{52}$$

Then the nonlinear formulation (50) can be converted to an equivalent linear as follows:

$$\begin{aligned}
& Min\ E[Z] + \tau(Z_{\max} - Z_{\min}) + \eta_1\left[D_1^{(3)} - \alpha D_1^{(1)} - (1-\alpha)D_1^{(2)}\right] + \eta_2\left[y\,D_2^{(3)} + (w_1 - y)D_2^{(2)} - w_1\,D_2^{(1)}\right] \\
& +\omega_1\left[\beta S_1^{(3)} + (1-\beta)S_1^{(1)} - S_1^{(1)}\right] + \omega_2\left[w_2\,S_2^{(3)} + (y - w_2)S_2^{(1)} - yS_2^{(1)}\right] + \gamma_1\left[\beta P_1^{(3)} + (1-\beta)P_1^{(1)} - P_1^{(1)}\right] \\
& +\gamma_2\left[w_2\,P_2^{(3)} + (y - w_2)P_2^{(1)} - yP_2^{(1)}\right] \\
& S.t: \\
& A_1 x \ge \alpha D_1^{(1)} + (1-\alpha)D_1^{(2)} \\
& A_2 x \ge (w_1\,D_2^{(1)} + (y - w_1)D_2^{(2)}) \\
& B_1 X \le \beta S_1^{(3)} + (1-\beta)S_1^{(1)} \\
& B_2 X \le (w_2\,S_2^{(3)} + (y - w_2)S_2^{(1)}) \\
& C_1 X \le \beta P_1^{(3)} + (1-\beta)P_1^{(1)} \\
& C_2 X \le (w_2\,P_2^{(3)} + (y - w_2)P_2^{(1)}) \\
& w1 \le My \\
& w1 \ge M(y-1) + \alpha \\
& w1 \le \alpha \\
& w2 \le My \\
& w2 \ge M(y-1) + \beta \\
& w2 \le \beta \\
& Y \in \{0,1\}, \qquad X \ge 0, \qquad 0.5 < \alpha, \beta \le 1
\end{aligned} \tag{53}$$

Where m is a predefined sufficient large number, which is called Big M in the literature. Also, the newly added constraints enforce that auxiliary variable vector w_1 is equal to zero when y=0; and is equal to α when y=1, the auxiliary variable vector w_2 also has the same condition.

5- Model implementation and numerical results

In this section, we demonstrate an application of our proposed mathematical model. The proposed model was optimally solved using CPLEX solver from the GAMS 24.1.1 optimization package on a computer with the following specifications: Intel Core i7 3610QM 2.3GHz and 8GB RAMDDR3 under win 10.

5-1- Case problem

Iran Khodro Company (IKCO) is an Iranian automotive corporation involved in the production and distribution of automobiles. IKCO was established in 1962, and it produced over 798,000 passenger cars in 2018. Vehicles manufactured by the company include Samand, Peugeot and Renault cars, trucks, and buses. ISACO is a subsidiary of Iran Khodro, which is involved in the distribution of spare parts of the automobiles manufactured by IKCO, which is selected for the study. At present, providing spare parts for automobiles is a must-have for the automotive industry. Customers are continually asking companies for spare parts, and their demand should be satisfied. It is a competitive advantage for a company to satisfy customer demand as soon as possible and with the best quality. Customer satisfaction is possible if the company has a highly efficient distribution network to distribute spare parts. In this paper, we want to optimize the distribution system of ISACO to establish social justice for customer zones.

We applied the presented framework in this paper to redesign the distribution system. The main stimulation that drove ISACO to optimally design its distribution network are as follows. First, ISACO tends to new infrastructures and distribution facilities like urban depots to make the distribution process faster and cheaper. also, the company aims to enter new markets such as middle east. moreover, high risks of uncertainty in different facilities and distribution elements (such as sanctions, currency fluctuations, etc.) encourage ISACO to make its distribution network more robust to such operational risks. Besides, the profitability and cost efficiency of producing products through assessment results justifies the redesign of the distribution network. ISACO has 31 main customer zones throughout the country and also has nearly 250 authorized dealers and trusted retailers as distribution centers all over the country. In this study, we want to optimize the distribution network of ISACO in Tehran province, which consists of 22 districts.

Here, a distribution system providing and supplying products to known customers is considered. ISACO is the main and official spare parts supplier for IKCO products, so its performance should be acceptable. ISACO must provide the parts from trusted suppliers and then, at the time of need, satisfy customer's demand through their distribution network.

In this research, we are looking to implement FLAP and trying to optimize ISACO spare parts distribution system. The central core of ISACO is located on the 13 km stretch of Karaj makhsous road, and it could be considered as a central warehouse. Spare parts are shipped from this core to various urban depots of the company throughout the country. then from these depots, the distribution of parts to official dealerships and retailers is done. Then, through the authorized dealers and trusted retailers, or generally through the official distribution centers, the products will be available to the applicant customers. The distribution of the authorized dealers and trusted retailers in Tehran are shown in figures 3 and 4.

Fig 3. Distribution of authorized dealers

Fig 4. Distribution of trusted retailers

In this article, we limit the study area to Tehran city, and it’s 22 districts. Due to the high cost of distribution, transportation, and storage of parts, ISACO has always been looking for the optimal locations of distribution facilities. due to the increase in IKCO production capacities and demand for spare parts from consumers, ISACO always sought to increase distribution capacities by increasing the number of central warehouses and urban depots.

ISACO distribution system is consists of five echelons, including part suppliers, CWs, UDs, authorized DCs, and CZs, as illustrated in figure1.

In this paper, we aim to estimate parameters close to the real-world case. Accordingly, all distances are accurately calculated using Google Map, unit shipping costs are estimated with a general approximation based on the average costs in authorized transportation companies, unit holding costs are determined based on the average costs of similar industrial depots, fixed opening cost of facilities in different districts are estimated based on the size of premises and request of industrial facility manufacturers, unit Shortage costs are determined based on interviews with the experts and customer relationship management department. In this study, demands are approximately calculated based on statistics provided by the Ministry of Industry, Mine, and Trade. Also holding capacities were determined based on information from similar industries and according to expert opinions and supply capacity as a percentage of maintenance capacity, moreover, supply capacity is considered based on historical data. In the section stochastic programming, to generate a fuzzy triangular number for a parameter, the first dimension of the fuzzy number is also the real-world parameters, but DM estimated the second and third dimensions of fuzzy numbers.

5-1-1-Determining values for indexes according to the case study

• Set of potential locations for urban depots:

Urban depots can be established in all 22 districts of Tehran, but the analysis is very complicated in all of the districts. So, using the multi-criteria decision-making methods, we select the five highest priority districts as potential locations for urban depots.

• Set of potential locations for central warehouses:

The central warehouses can also be established in most industrial areas of Tehran under the location requirements considerations, but to simplify model calculations based on the Topsis method, we consider three points as potential locations to establish central warehouses. These potential regions are Karaj makhsous road, Abbas Abad industrial region, and KHAVARAN industrial region.

• Set of products:

Due to the wide variety of products, we categorized the products into four categories, including consumable parts, engine parts, hulk parts, and electronic parts.

• Set of distribution centers:

Distribution centers, including all authorized distributors and trusted retailers of ISACO and IKCO, which the number is estimated at 120. To avoid increasing problem dimensions, after removing the dealership and combining the demand of the nearby stores, finally, we consider 6 points that are six superiors made by ISACO as candidate locations.

• Set of planning horizons or time periods:

Considering that warehouses and depots capacity is on a monthly basis, each time period is regarded as a month. The problem is executed in five months.

•Set of customer zones:

Considering that all applicants in the 22 districts of Tehran are admitted as customers of the distribution system, to simplify the analysis, the customer zones are grouped into six clusters.

Based on the above description, the sizes of real-world case study dataset are illustrated in table 2

Table 2. Specifications of case study dataset

$\lvert I\rvert$	$\lvert J\rvert$	$\lvert K\rvert$	$\lvert L\rvert$	$\lvert M\rvert$	$\lvert R\rvert$	$\lvert S\rvert$	$\lvert T\rvert$
3	5	4	6	6	5	5	5

According to the above-mentioned case study, the locations of existing and candidate facilities and market zones involved in the distribution network of ISACO in Tehran are illustrated in figure 5.

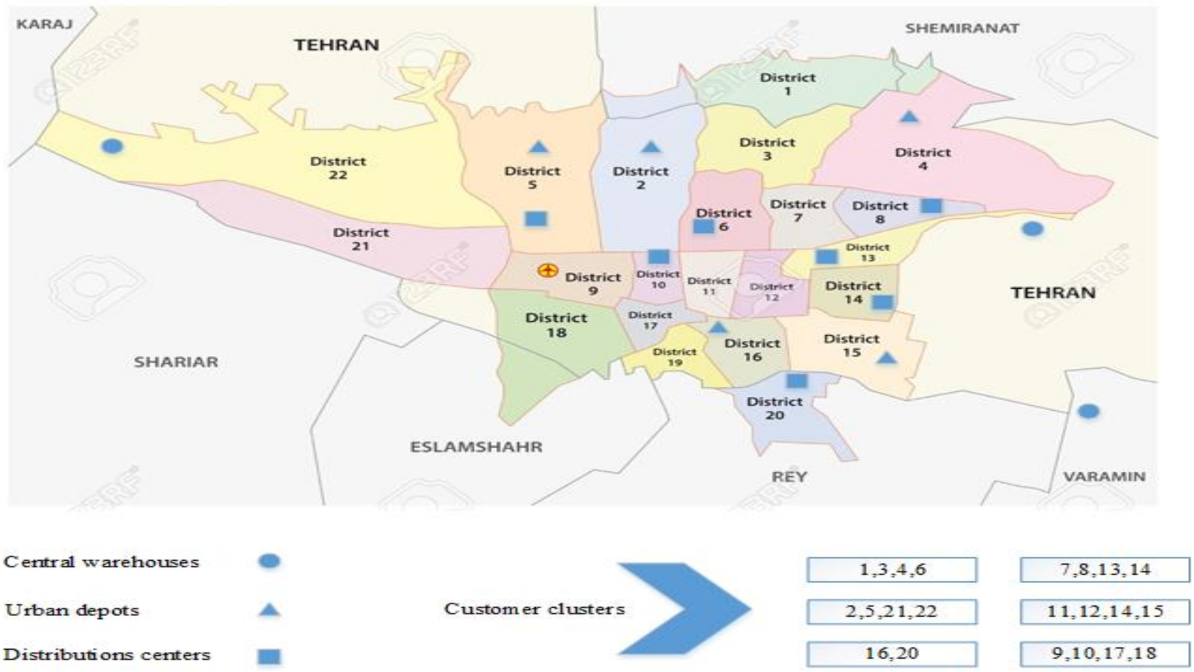

Fig 5. Locations of different existing and candidate facilities involved in ISACO's distribution network

5-2- Evaluation and implementation

We implemented the proposed model to determine optimal distribution network design decisions for ISACO Company. Figure 6 illustrates the optimal location-allocation decisions for central warehouses, urban depots, distribution centers, and customer zones. The optimal solution requires establishing a central warehouse in Makhsous road industrial estate. The new urban depots are located in districts 2,4 and 15. The demands of customer clusters are allocated to existing distribution centers. All of the location-allocation decisions are illustrated in figures 6 and 7.

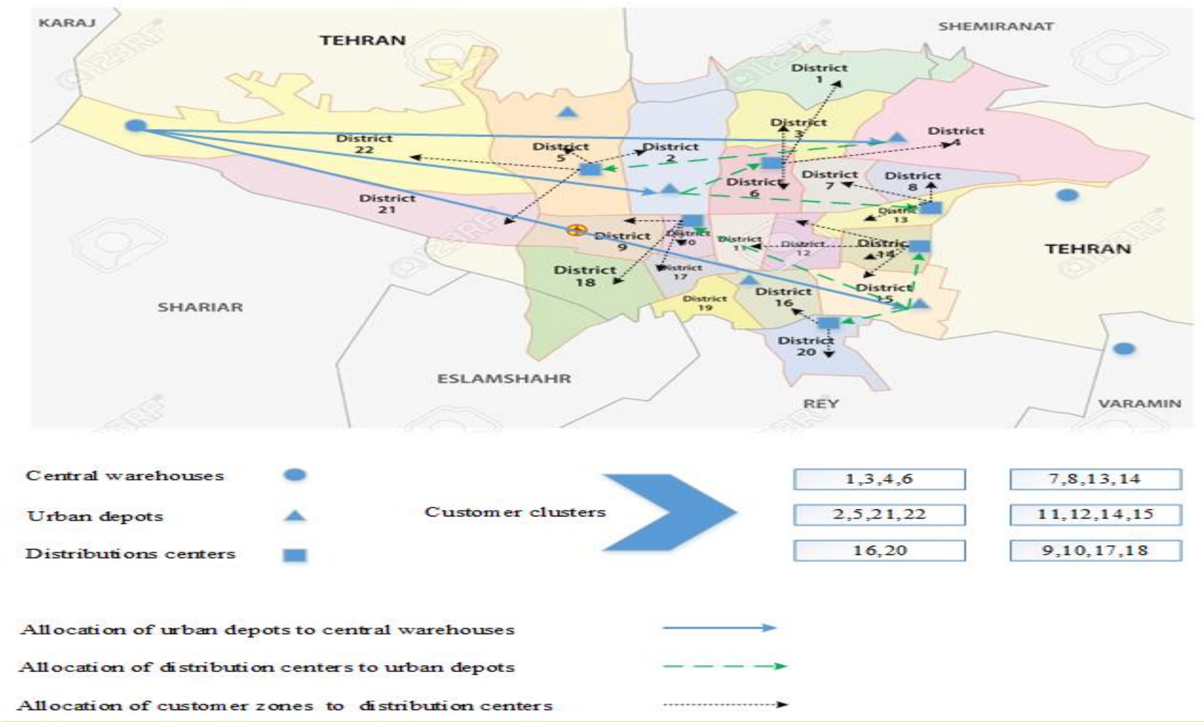

Fig 6. Optimal location and allocation decisions based on the most probable disruption scenario

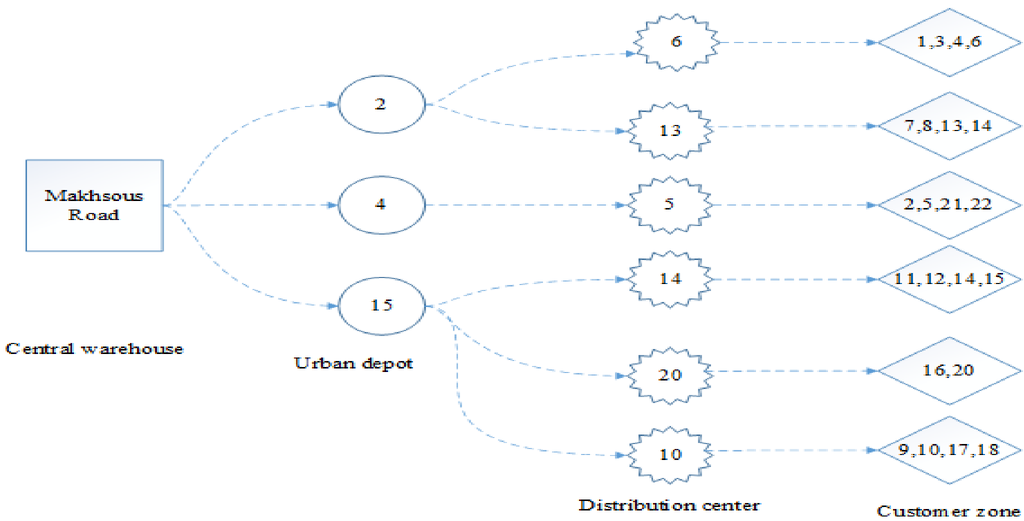

Fig 7. Optimal location and allocation decisions based on the most probable disruption scenario

5-2-1-Sensitivity Analysis

5-2-1-1- Pareto frontiers based on the partial robust model

Multi-objective problem formulation is justifiable if there is a remarkable conflict among the objective functions. Therefore, if there is no conflict among objective functions, we need to rethink mathematical modeling and convert the problem to a single objective one. To this aim, we must have just a single objective and consider the remained objectives as new constraints.

Based on the above-mentioned content, to investigate the conflict between each objective function pairs, we plot each objective in terms of another objective and examine the behavior of the graph. The two objective pairs conflict if the plotted Pareto frontier behave strictly increasing or strictly decreasing (Wang et al, 2018). In this regard, given that we have three objective functions, we must plot 3 Pareto frontiers, based on the results of the ε-constraint method. It should be noted that by altering the epsilon bound vector along the Pareto frontier and making a new optimization problem for each new vector, the Pareto optimal set can be achieved (Dehghani et al, 2018a). The generation of different points of the Pareto frontier using different values of the upper and lower ε bounds are illustrated as follows:

Figure 8 investigates the conflict between first and second objective functions. Given that the illustrated Pareto frontier behaves strictly decreasing in figure 8, there is a significant conflict between the total distribution system cost and the total environmental impact. The more we spend budget on the distribution network, the more we can cope with lost sales or holding of inventory, which naturally leads to a reduction in the transportation of parts and, therefore, the environmental impact.

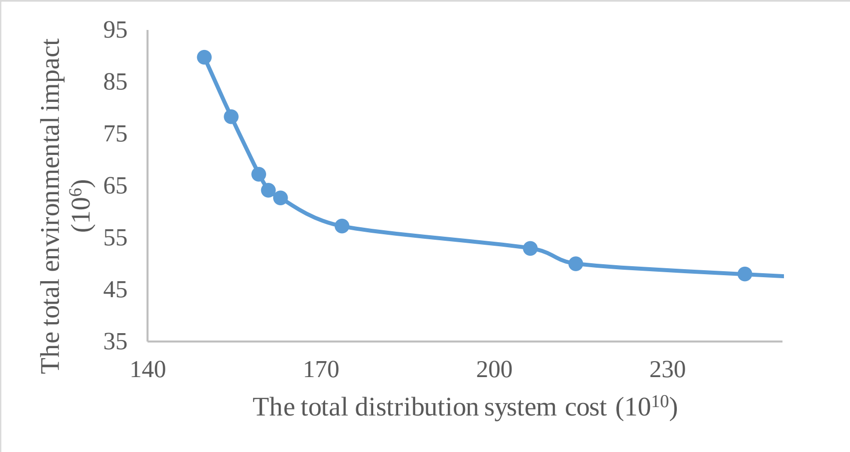

Fig 8. Conflict between the total distribution system cost and the total environmental impact

Figure 9 shows the conflict between the first and third objective function. Given that the illustrated Pareto frontier behaves strictly decreasing in figure 9, there is a remarkable conflict between the total distribution system cost and the minimum of a maximum lost sale. In fact, the more we spend budget on the distribution network, the more we can deal with the shortages and also holding of inventory, which naturally leads to a reduction in the minimum of the maximum lost sale in customer zones.

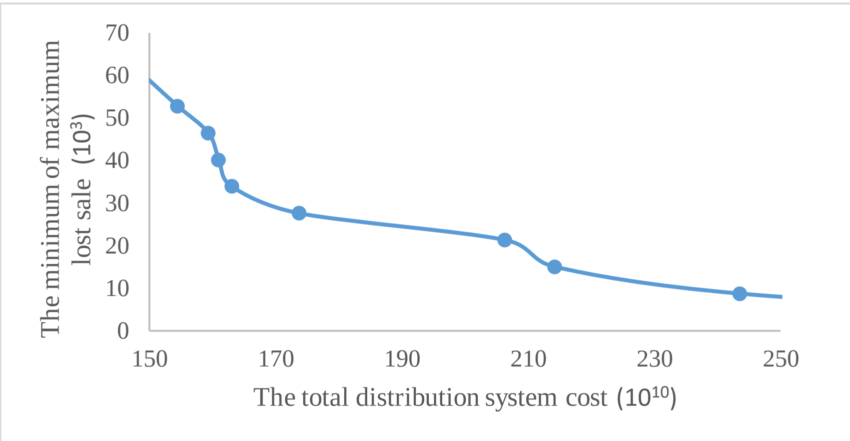

Fig 9. Conflict between the total distribution system cost and the minimum of a maximum lost sale

Figure 10 investigates the conflict between the second and third objective function. Given that the represented Pareto frontier behaves strictly increasing in figure 10, there is a significant conflict between the total environmental impact and the minimum of the maximum lost sale. Indeed, the more shortages occur, due to the high shortage costs, the distribution network tries to transport more products to different echelons of the distribution system, which will increase the total environmental impact.

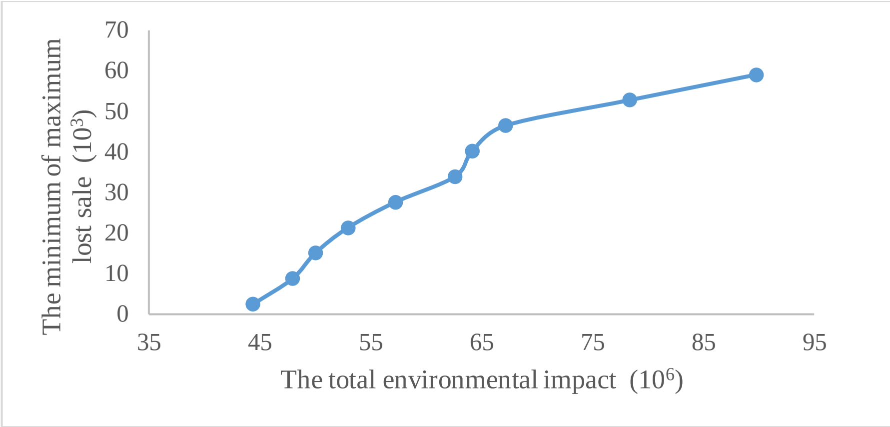

Fig 10. Conflict between the total environmental impact and the minimum of a maximum lost sale

5-2-1-2-Analysis of the impacts of shipping capacity and holding capacity

After solving the model, to check the behavior of the model against variations, we need to execute the sensitivity analysis. For this purpose, we need to evaluate the results of varying some specific parameters in the model. Those parameters can be investigated to the analysis that are exogenous, and the company has no control over them. Under the rules of ISACO corporation, the distribution centers of ISACO are usually left to real people, and therefore companies cannot accurately monitor the status of these centers at any given time, and thus parameters such as holding capacity and shipping capacity of distribution centers are considered exogenous parameters in this problem, and the model behavior can be investigated by varying them.

Figure 11 illustrates how changes in the shipping capacity of distribution centers can influence all three objective functions, including the total distribution system cost, the total environmental impact, and the minimum of the maximum lost sale. By increasing the shipping capacity of distribution centers, the system will be gradually reduced to a minimum, the total distribution system cost, and the total environmental impact, which is quite logical, because the more products are distributed by distribution centers, the less system will face shortages and the cost of lost sales will decrease. On the other hand, distribution centers will provide more inventory of products, resulting in less need for transportation, and also the total environmental impact will reduce.

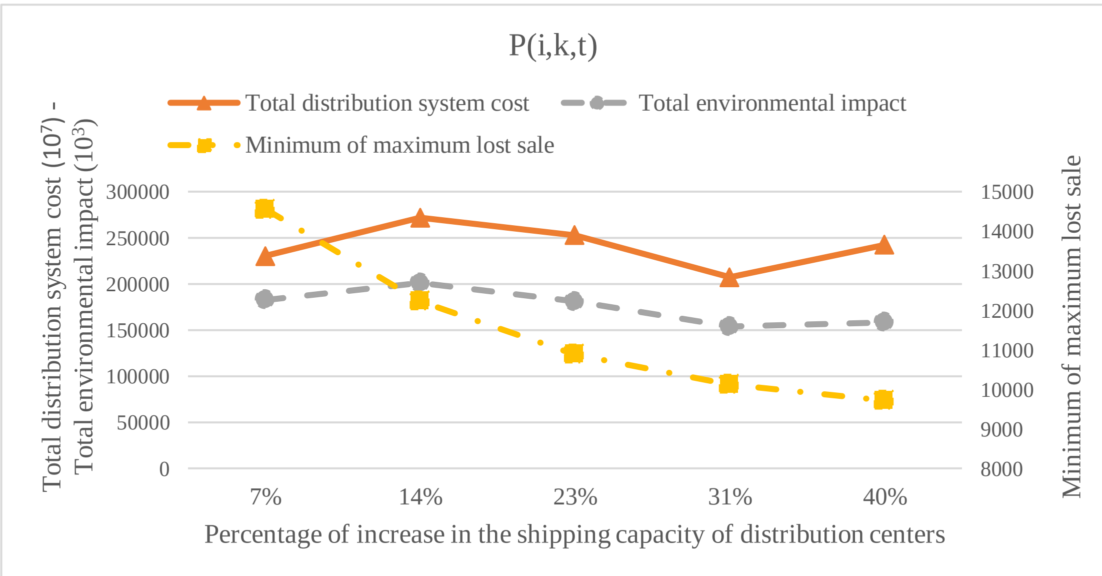

Fig 11. The impact of varying the shipping capacity of distribution centers on objectives

Figure 12 illustrates how changes in the holding capacity of distribution centers can influence all three objective functions. By increasing the holding capacity of distribution centers, both the total distribution system cost and the minimum of the maximum lost sale will decrease, which is logical. The total environmental impact doesn't have an apparent behavior. The reduction of the first and third objective is because the more the holding capacity increases, the less system will face lost sales. Also, shortage costs will decrease, moreover, distributors will hold more stock, and consequently, there will be less need for transportation, and the total environmental impact will decrease.

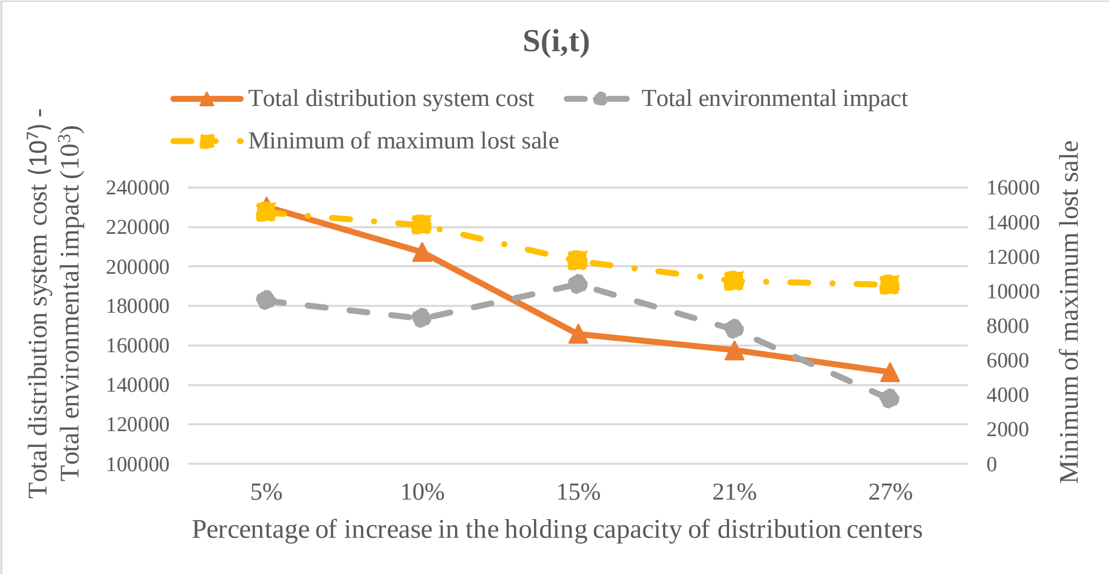

Fig 12. The impact of varying the holding capacity of distribution centers on objectives

Given that the sensitivity analysis results are entirely reasonable, the proposed model can be considered to be valid and appropriate.

5-2-1-3- Examining model complexity

The model complexity can be examined based on a variety of aspects, including the number of binary variables, the value considered for big m as a parameter, problem dimensions, the execution time, etc. In this study, we consider the complexity of the proposed partial robust model based on execution time, and we aim to investigate the model complexity by varying problem dimensions and also parameter Big M. As illustrated in figures 13-14 and Table 3, by increasing the problem dimension or the considered value for big M, the problem execution time and consequently the model complexity increases so that when we want to execute the proposed model in a large scale, it is not possible to solve the model using ordinary computers and processors.

Table 3. Considering the model complexity

Run	Big M	Execution time	Run	Dimension	Execution time
1	10^6	0.0363	1	6×5×3×4×5×6	0.0363
2	10^7	0.047916	2	7×6×4×5×6×7	0.042108
3	10^8	0.059416	3	8×7×5×6×7×8	0.052214
4	10^9	0.102789	4	9×8×6×7×8×9	0.068922
5	10^10	0.171658	5	10×9×7×8×9×10	0.080639
6	10^11	0.192257	6	11×10×8×9×10×11	0.087897

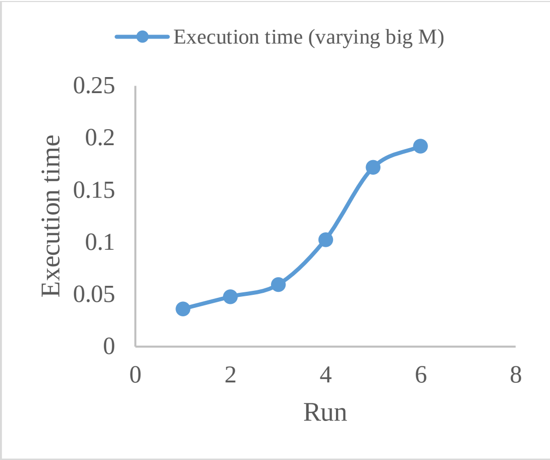

Fig 13. The effect of varying the Big M in terms of execution time on the model complexity

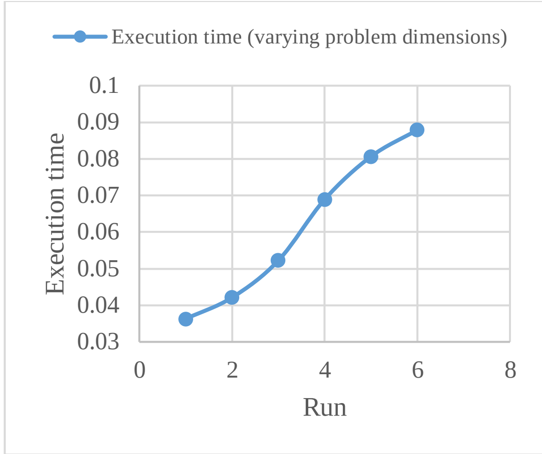

Fig 14. The effect of varying the Big M in terms of execution time on the model complexity

5-2-2- The achievement of the proposed two-stage robust formulation

This section aims to discuss how the developed two-stage robust possibilistic programming model can assist in decreasing the total distribution cost, the total weighted distance traveled, and the maximum lost sales for customer zones in ISACO. Mathematical modeling in the above-mentioned problem has been accomplished based on three approaches, including deterministic, partial robust, and impartial robust optimization.

Figure 15 investigates the results of optimized three objective functions based on deterministic, partial robust, and impartial robust approaches. The impartial robust method leads to the highest amount of total distribution cost and total weighted distance traveled in the distribution network, and also the lowest minimum of the maximum lost sale in customer zones. Altogether, utilizing robust possibilistic programming causes better performance than the deterministic approach. Based on the comparisons and the nature of minimization in objective functions, the partial robust approach has the best performance in the proposed model, and this method is considered as the basis of modeling in this research. Therefore, all analysis are executed based on the results of partial robust.

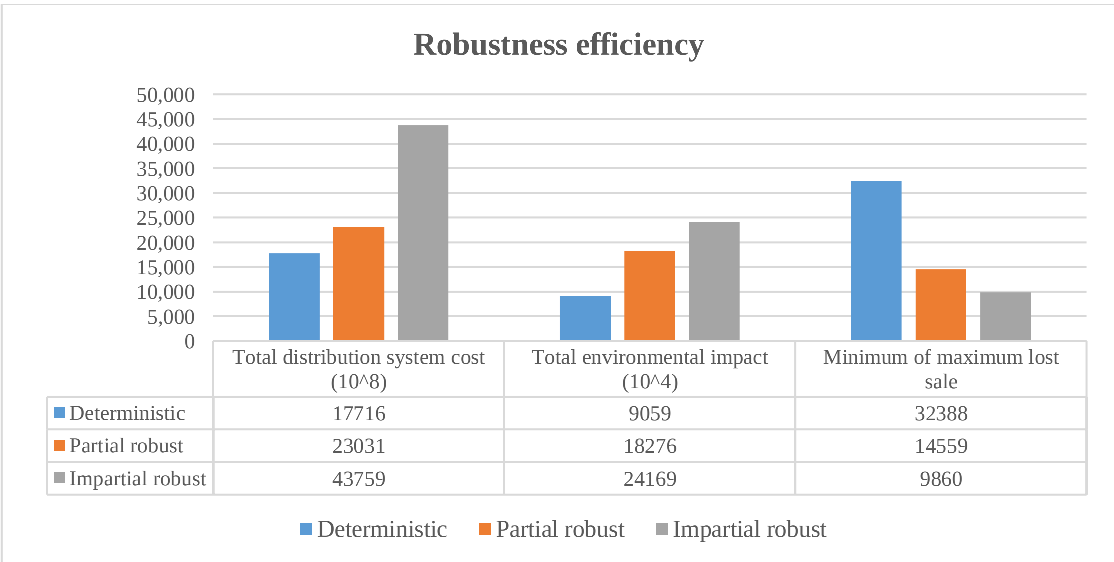

Fig 15. Comparing the performance of the deterministic, partial robust and impartial robust approaches

5-3- Investigating the validation of the proposed model

After the model implementation and obtaining results, we must examine the validity and accuracy of the proposed mathematical model. To this aim, there are some procedures, including simulation process, statistical analysis, expert opinions, and group decision making, Comparing the results of the model with historical data, etc. In this study, the infeasibility simulation process and expert opinions are utilized to validate the proposed model.

5-3-1-Infeasibility simulation process

In this paper, we used a simulation process to validate both deterministic and partial robust models. To this aim, we consider all parameters of the model as a triangular fuzzy number, and we replace all parameters with their fuzzy expected values. In this case, we execute both robust and deterministic models and consider the solutions as the model basis. The simulation experiment was executed in 200 runs and parameters *D(l,k,t)*, *D(i,k,t)*, *S(i,t)*, *P(i,k,t)*, *P(k,t)* were randomly generated in each execution.

In each iteration, given the minimization nature of the objective functions, we add infeasibility penalties to basic values of objective functions using logical unit penalty rates (Dehghani et al, 2018a). The basic values, the values per simulation iteration, the mean and standard deviation for all three simulated objective functions are represented as follows:

Table 5 illustrates the calculated values for objective functions based on the partial robust and deterministic approaches in the primary model.

Table 5. Calculated values for objective functions based on the primary problem

Problem condition	Economic (10^8)	Environmental (10^4)	Social justice
deterministic	17716	9059	32388
partial robust	23031	18276	14559

Figure 16 illustrates the average simulated objective functions based on both deterministic and partial robust model are so close to their basic values but merely relying on the amount of the average simulated objective functions cannot prove the validity of a mathematical model and in fact, can only be claimed by examining the standard deviation values of the simulated objective functions.

For the next step, the standard deviation will be determined for simulated objective functions based on both deterministic and partial robust models. If the standard deviation values are acceptable, we can verify the model validation.

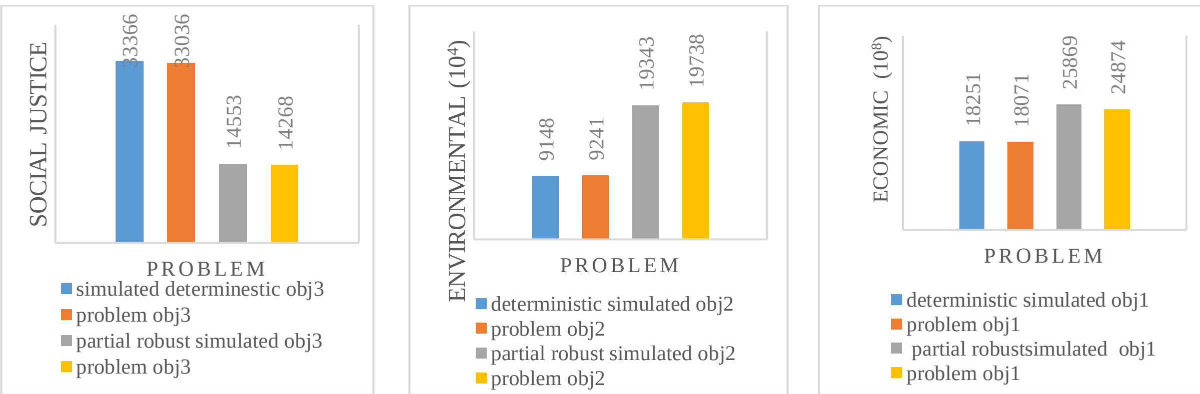

Fig 16. Comparing the average simulated objective functions with basic values

Figure 17 enforces that the calculated standard deviation values for the simulated objective functions in the partial robust model are lower than the standard deviation values in the deterministic model, so the presented mathematical model is valid, and this paper can be cited.

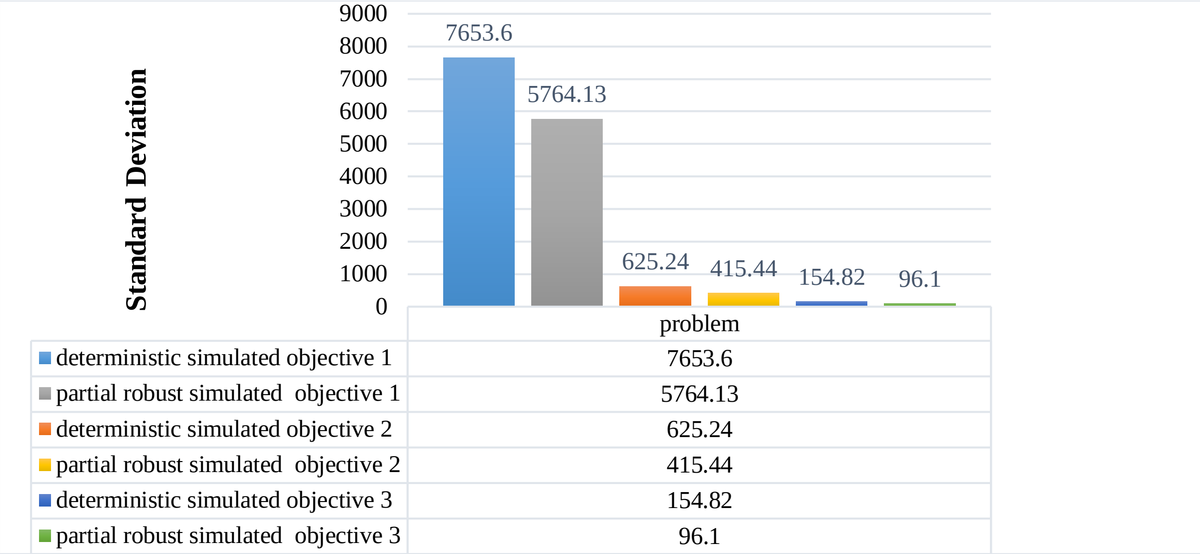

Fig 17. Determining the standard deviation of all simulated objectives

5-3-2- Expert opinions and historical data

After the model implementation, numerical and managerial results were obtained, and this information was provided in the form of a detailed report to executives in both ISACO and IKCO companies. After reviewing the results by experts and comparing the behavior of the mathematical model with the behavior of historical data, the company experts confirmed that the model presented in this research is significantly valid and accurate. Experts acknowledged that the numerical results of this study would be useful to extend and redesign the current distribution system.

6-Conclusion

This paper studied the SCND problem for a five-echelon forward distribution system, which is vulnerable to uncertainty and disruption risks. We presented a novel two-stage robust possibilistic programming model that can be utilized to minimize the total distribution system cost, the total environmental impact, and the minimum of the maximum lost sale occurred in customer zones, which is converted to a single objective model using an Epsilon single-minded restriction. The robust model enables the distribution system to cope with uncertainty, and operational risks, and the disruption considerations are applied using two-stage stochastic programming. It should be noted that we take into account simultaneous disruption in facilities, including supplier clusters, central warehouses, urban depots, distribution centers, customer zones, and routes among them (multiple disruptions).

The model decisions include locating central warehouses, and urban depots, and determining the amount of different products transport between various nodes of the network, and the number of lost sales for different products in each market zone. Also, the possibility of complete disruption of facilities and their limited capacity were considered. We used real data based on a real-world case study to examine the performance of the proposed model in designing an efficient forward distribution network involved in the distribution of the spare parts of automobiles. Based on the numerical results, we found that Although the two-stage partial robust approach in the short term can appreciably increase all three objective functions to cope with uncertainty and disruption, it will be useful in the long run by reducing the costs of dealing with operational and disruption risk as well as decreasing shortage costs.

Despite the critical and useful insights from the model implementation, our study is not without limitations. For example, distribution systems are always vulnerable to random disruptions. Thus, it can be incorporated into various resilience strategies into the proposed model to cope with disruptions. Resilience strategies can include the fortification of facilities against disruptions, outsourcing, multiple sourcing, considering excess capacity, providing backup facilities, etc. Besides, taking into account different concepts such as sustainability can be interesting future research avenues. The inclusion of the social consideration dimension of sustainability in this model can also provide additional and useful insights. Moreover, the shortage of products can be considered as a backlog, and the company should be committed to compensate these shortages as soon as possible. Most of the previous studies on supply chain network design under operational and disruption risks have focused on introducing and using various strategies to deal with disruption risks at facilities while there is scanty literature on measurement of the network resiliency, so based on the mentioned limitation in supply chain network design under risk, some network resiliency measures such as node criticality, flow complexity and node complexity should be taken into account. Incorporating operational decisions such as scheduling and travel times into our proposed model also can be proper further research. It should be noted that in our model for large sizes, considering appropriate solution approaches, including lagrangian relaxation and Benders decomposition, is another future research.

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