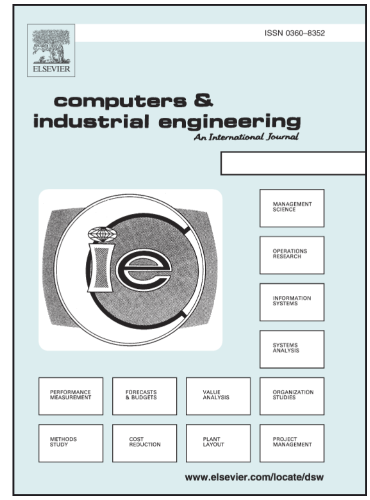
Journal Pre-proofs



Multi-objective sustainable opened- and closed-loop supply chain under mixed uncertainty during COVID-19 pandemic situation

Arijit Mondal, Sankar Kumar Roy

PII: S0360-8352(21)00357-0
DOI: https://doi.org/10.1016/j.cie.2021.107453
Reference: CAIE 107453

To appear in: *Computers & Industrial Engineering*

Received Date: 27 September 2020
Revised Date: 12 April 2021
Accepted Date: 3 June 2021

Highlights:

- Sustainable opened- and closed-loop supply chain is designed in mixed uncertainty.
- Demand priorities of COVID-19 areas are derived and utilized.
- Transportation and pick-up-delivery vehicle routing problem are considered.
- An uncertain-random robust optimization approach is developed.
- Three test problems are implemented and sensitivity analyses are provided.

Multi-objective sustainable opened- and closed-loop supply chain under mixed uncertainty during COVID-19 pandemic situation

Abstract

Logistics problems play a significant role in an emergency situation. During and after a critical circumstance (like pandemic COVID-19), it is an important task to active the opened- and closed-loop system through an efficient and resilient supply chain network. This paper considers a *multi-objective multi-product multi-period two-stage sustainable opened- and closed-loop supply chain planning* to maintain supply among production centers and various hospitals during COVID-19 pandemic situation. To build a less contagious network, transportation problem and pick-up-delivery vehicle routing problem are designed as two stages, respectively to carry out distribution. We allow a mixed uncertain environment by considering uncertain-random parameters in the proposed model to express ambiguity in real-life data. A multi-attribute decision making approach is suggested to determine the priorities of affected areas, according to their urgency in terms of entropy weights. Moreover, a robust optimization approach for uncertain-random parameter is developed to cope with uncertainty in different scenarios, and thereafter augmented weighted Tchebycheff method is applied to solve the model. To demonstrate the practicability of the proposed model and solving approach, three test problems with reasonable sizes are considered and results are discussed through some sensitivity analyses.

Keywords: Sustainable opened- and closed-loop supply chain; Mixed uncertainty; Multi-attribute decision making; Transportation problem; Pick-up-delivery vehicle routing problem; Robust optimization.

1 Introduction

Planning a suitable production and distribution system (PDS) is very difficult as well as important during critical situation for providing necessary goods to consumers. Again, planning in emergency situations are different from business planning in various ways ([32]): *(i)*

Preprinted for submitting in Computers & Industrial Engineering.

absence of previous experience, *(ii)* proper information may not available, *(iii)* resources and requirements may not be available to maintain the supply chain (SC), *(iv)* there are various risks to carry out SC and limited time to resolve those, *(v)* complicated system management may lead the PDS into serious trouble. Sustainable supply chains become a research trend nowadays, because of its concerns about economical, environmental and social impacts. In critical lock-down situations during affect of COVID-19, a SC should be designed to resolve the main issues about shortages of budget and raw materials, late delivery, unsatisfied demands (UDs) and unemployment; therefore the sustainable closed-loop SC (SCLSC) would be a better option. However, the environmental impacts (EIs) are not so much concerning issue in this situation as most of the public transports are stopped. Hence, the primary goals of the SC administrators should be to satisfy demands within a suitable time by increasing employments, also by keeping in mind the budget.

According to the literature of SC, there are mainly three types of SC network: *(i)* forward, *(ii)* reverse, and *(iii)* closed-loop SC (CLSC), in which first two also can be recalled as opened-loop SC (OLSC). Emergency logistics problems mainly focus to the OLSC, however in the emergency circumstances due to usual shortage of new raw materials and budget, and high demands, reusable products should be recovered and reproduced to be used again, therefore, as a result, reverse flows should be incurred in synergy with forward flows. Also, researchers ([9], [11], [25]) have explained the fact that there are more job opportunities in reverse network (RN) than the forward network (FN). As a thought of these facts, the proposed PDS is designed with collaboration of opened-loop (OL) as well as closed-loop (CL) by integrating existing studies on SC, reverse logistics (RL), and humanitarian logistics (HL), in which economical, satisfactory and social aspects are taken into consideration. Then the problem becomes sustainable opened- and closed-loop supply chain (SOCLSC). The proposed SOCLSC network consists of two types of products, non-reusable products (NRPs), which flow from production-distribution centers to hospitals through transfer-collection centers (TCCs) in OL forward network, and reusable products (RPs), which flow from production-recovery-distribution centers to hospitals through same TCCs in forward network and after used, flow back to disposal and production-recovery-distribution centers from hospitals through TCCs in reverse network (thus the CL network is formed with only RPs).

In the recent years, SCLSC becomes more popular among researchers and company managers due to its versatile competitive advantages. Economical impacts of SCLSC help the companies to take right strategic and planning decisions for achieving profit, making new employments, supplying raw materials or delivering products. On the other hand, considering social impacts (SIs) help to make a nice public image for the companies to get competitive advantages ([25]). Actually, choosing sustainable impacts which get the SC network design more closer to the real applications. Recently, Das et al. [4] applied type-2 intuitionistic fuzzy (T2IF) logic to a green solid transportation-location problem (TLP) by considering carbon tax, cap and offset policy. Liao et al. [13] took into account economical and environmental issues in a CLSC network for citrus fruits crates. Maity et al. [18] developed a sustainable time-variant multi-objective transportation problem (TP) in interval environment. Considering economical and environmental aspects, Alegoz et al. [2] designed a CLSC network.

Most general objectives considered by previous researchers for a logistics problem in disaster response or in SCLSC are minimizing total cost (maximizing profit), minimizing time, minimizing backlog quantity (BQ), minimizing carbon emission, maximizing employments, maximizing satisfaction of demand points, etc. Tzeng et al. [35] formulated a multi-objective model for relief delivery by considering minimizing total cost, minimizing total travel time and maximizing satisfaction as three objectives. Gilani and Sahebi [11] designed a sustainable supply network with maximizing profit and employments, and minimizing EIs. Considering composite weights for three objective functions, cost, time and satisfaction of demands, Liu and Zhao [15] solved an emergency logistics problem. Soleimani et al. [33] demonstrated a RL problem by pick-up and delivery with reducing pollution and cost and solved by fuzzy programming (FP). Haghani and Oh [12] minimized total cost in a multi-commodity multi-modal network for disaster relief operations. Afshar and Haghani [1] constructed a logistics model for disaster response and aimed to minimize the weighted sum of UD as objective. Based on the above views, we motivate to formulate an emergency SOCLSC network which minimizes total cost of production, distribution and inventory, total distribution time in forward and reverse flows, total BQ weighted by demand priorities (DPs), and maximizes total created employments.

For distribution network in SC or logistics problems, most of the previous studies were formulated as TP, and a few of them was constructed as vehicle routing problem (VRP) or location-routing problem (see Table 1). Maity et al. [19] analyzed a multimodal TP by showing its application to artificial intelligence. Zhalechian et al. [38] designed a sustainable closed-loop location-routing-inventory supply chain network under stochastic-possibilistic environment. VRP with spilt demands was used in reverse logistics by Eydi and Alavi [8] and solved by simulated annealing (SA). Recently, Midya et al. [20] formed a multi-stage multi-objective fixed-charge solid TP in a green supply chain in intuitionistic fuzzy environment. Actually, there are not enough diversity in the network design of supply chain in the existing researches. Here we contemplate that, only one TCC can be situated in each affected area/city, and all hospitals in this area/city are covered (deliver and collect) by this TCC. Furthermore, distance between the TCC of an area/city and hospitals of another area/city is often very long, so transaction between two different areas/cities can be more time and cost consuming, and it is also unreasonable due to contagious nature of COVID-19. Regarding these facts, we consider TP (as first stage) as well as pick-up-delivery VRP (PDVRP) (as second stage) to distribute and collect products.

Handling the uncertainty in the parameters is a typical issue in a real-life logistic problems as wrong estimation of parameters leads to higher losses in an unpredictable and undesirable circumstance. Many distribution problems under various uncertainties were studied previously, some of them are described here. Fathollahi-Fard et al. [9] formulated forward/reverse logistics network, and Mahapatra et al. [17] formed multi-choice TP in stochastic environment. Tofighi et al. [34] designed a HL network under mixed uncertainty (possibilistic-stochastic) and solved by possibilistic-stochastic programming (PSP) and differential evolution (DE). Roy and Maity [28], Roy and Midya [29], Roy et al. [30] and Roy et al. [31] designed various types of multi-objective TPs in interval, intuitionistic fuzzy, random-rough and fuzzy-rough environments, respectively. Mirzapour et al. [21] used robustness to handle uncertainty in SC. Das and Roy [3] solved a multi-objective green transportation-p-facility location problem under neutrosophic environment. Sometimes, due to lack of information, proper values of the parameters could not be acquired, and only probability distributions are not sufficient to estimate the parameters, so the decision maker has to provide such type uncertainty which is a blending of historical data and belief degree to describe the parameters. Again fuzzy concepts fail to quantify some indeterminate quantities like the bridge strength (see [14]). Also in our best of knowledge, no previous study on SC is formulated in uncertain-random environment. Motivated by the above facts we assume some parameters as uncertain-random parameters, first proposed by Liu [16], which is an efficient tool to handle two-fold ill-known quantities.

Among the affected areas it is likely that there are different levels of urgency for allocation of products. Such urgency can be taken into account by considering different attributes described in subsection 4.1. Inspired by Mon and Cheng [23], we propose a multi-attribute decision making (MADM) approach, intuitionistic fuzzy analytic hierarchy process (IFAHP), to determine urgency degrees (in terms of DPs) of affected areas in the form of entropy weight priorities. AHP represents the elements of a problem hierarchically and is used to derive priorities among criteria. For more details about AHP one can see Mon and Cheng [23]. Utilizing these priorities, the parameters related to the affected areas are estimated which is explained in subsection 6.2.

Some of the previous methods, which are applied to solve deterministic and uncertain SC models, are mentioned here. Nayeri et al. [25] formulated a SCLSC network by optimizing economical, environmental and social impacts and solved by multi-choice goal programming

with utility function (MCGP-UF). Dehghan et al. [6] applied hybrid robust stochastic-possibilistic programming approach to solve a CLSC problem. Gholizadeh et al. [10] applied multi-objective genetic algorithm (MOGA) to solve CLSC problem. Das et al. [5] used heuristic algorithm (HA) to solve a solid transportation-p-facility location problem. Entezaminia et al. [7] used L-P metric method to solve a multi-objective multi-product multi-site production planning problem. Recently, fuzzy-robust (robust-possibillistic) optimization became very popular to deal with uncertainty as well as to solve the SC problem ([11], [25], [27]). RO through scenario decomposition is one of the most efficient robust techniques to handle scenario-based uncertainty and to solve the production-distribution problem under uncertainty. Adopting this approach, we develop a RO approach through decomposing scenarios of uncertain-random variable in this paper to solve the SOCLSC model, which is then solved by augmented weighted Tchebycheff method (AWTM).
In brief, this paper suggests a multi-objective mixed integer programming (MOMIP) model to describe a two-stage SOCLSC in mixed uncertainty, which considers multiple periods and multiple products. The uniqueness of the contributed model can be found in the network structure, where two types of products can flow in parallel way, also both new (original + recovered) and returned RPs can be simultaneously distributed and pick-up (see Fig. 1). To the best of our knowledge, such network is not designed in the available literature.

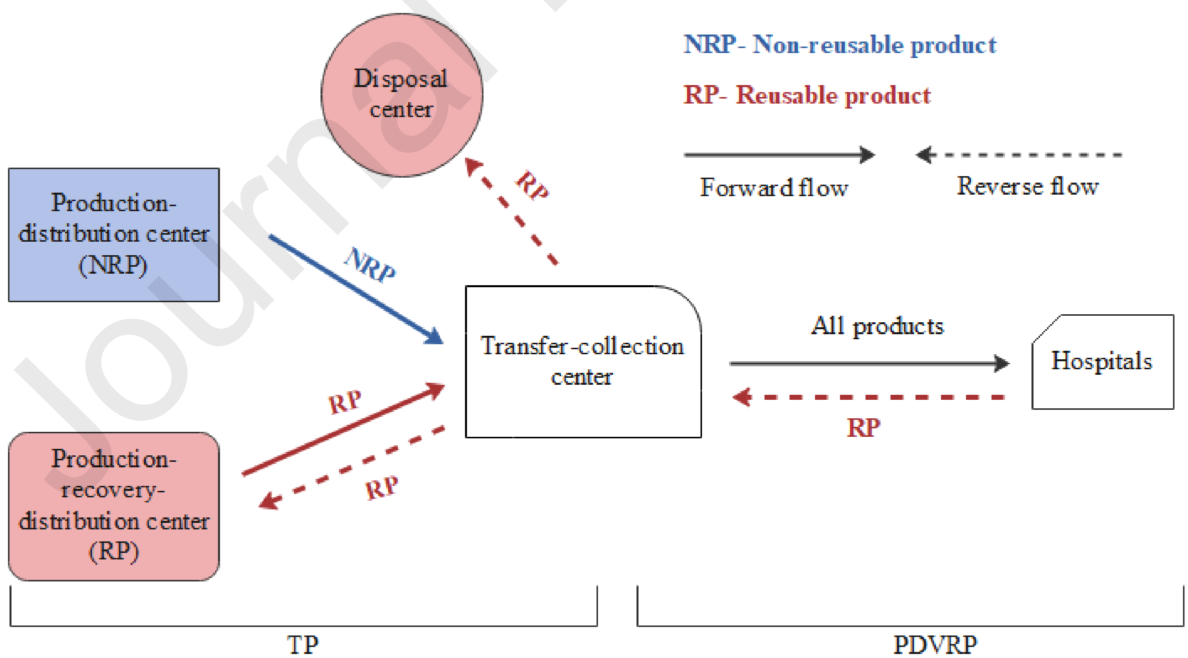


Fig. 1: Framework of the proposed network.

► **Research gap analysis**

A summary of reviewed related literature can be seen in Table 1. By going through Table 1 and remembering existing literatures, some gaps of the past researches can be identified as follows:

- Most of the studies were formulated with one type of product i.e. RP or NRP in CLSC but in real-life, for various purposes a CLSC network may contain RP as well as NRP. Also most of the previous researches were designed as single product CLSC network which is not suitable for a comprehensive SC network in an emergency situation.
- Single objective and/or single period CLSC networks were designed by most of the previous researchers. But in real-world problems, due to conflicting situations single objective is not suitable to achieve the goals, also considering single period cannot figure out the practical SC system properly.
- As distribution network, most of the researches were designed as TP and/or location-allocation or PDVRP, but TP and PDVRP should be simultaneously designed in a two-stage SC during COVID-19 situation to provide more contact-less service.
- In most of the studies, either uncertainty was not considered or uncertainty was considered in specific parameter (parameters) or single fold uncertainty was considered. But in practical situations uncertainty usually occurs not only in some specific parameters but also in almost all parameters and in some unpredictable and critical situations only single fold uncertainty is not able to estimate the parameters properly.
- Logistics problems during an emergency situation were usually formulated previously as OL network, but in an unprecedented situation (e.g., COVID-19 lock-down) an SOCLSC network would be better option than only OL network.
- Demand priority was not calculated or utilized in most of the previous studies, but it is obvious that demand points may have different urgency degrees.

▶ **Contributions of the research**

To fill in the gaps which are seemed in previous researches in all possible ways, this study is contributed, and the outlines of the major contributions are as follows:

- Offering a new MOMIP model which describes a multi-objective, multi-product, multi-period, two-stage SOCLSC during the situation of COVID-19 by considering economical, satisfactory and social aspects.
- Uncertainty in the parameters are tackled by considering uncertain-random environment.
- Suggesting an MADM by IFAHP to determine priorities of affected areas in terms of entropy weights.
- Formulating TP as well as PDVRP simultaneously in a single SC network, to carry out distribution and collection in a less contagious way.

- Developing an equivalent robust counterpart model and solving it by AWTM.
- Deliberating three test problems, and finally studying results with some sensitivity analyses to show the applicability of the stated problem.

The remaining paper is structured as follows: Some necessary preliminaries are given in Section 2. Section 3 describes the motivation for considering uncertain-random parameters, and the proposed problem is presented in Section 4. The uncertain-random robust optimization technique as well as the solving procedure is given in Section 5. In Section 6, computational experiments for three test problems are given to illustrate the feasibility and effectiveness of the proposed model. Section 7 ensures the importance of the research by providing some managerial implications. Finally, Section 8 delivers some concluding remarks and future scopes.

2 Preliminaries

In this section some elementary concepts are discussed which are essential to proceed for further study.

Definition 2.1 *[14] Let Δ is a non-empty set and $\mathcal{A}$ is a σ-algebra over Δ. $\mathcal{M}$, a set function from $\mathcal{A}$ to $[0,1]$ is called an uncertain measure if it satisfies the following axioms:*
(i) $\mathcal{M}\{\Delta\} = 1$ for the universal set Δ (Normality axiom).
(ii) $\mathcal{M}\{\Theta\} + \mathcal{M}\{\Theta^c\} = 1$ for any event Θ (Duality axiom).
(iii) $\mathcal{M}\left\{\bigcup_{\iota=1}^{\infty} \Theta_\iota\right\} \leqslant \sum_{\iota=1}^{\infty} \mathcal{M}\{\Theta_\iota\}$ for every countable sequence of events $\Theta_1, \Theta_2, \ldots$. (Subadditivity axiom).
Then the triplet $(\Delta, \mathcal{A}, \mathcal{M})$ is called an uncertain space. Moreover $\mathcal{M}$ also satisfies the product axiom stated as:
(iv) Let $(\Delta_\ell, \mathcal{A}_\ell, \mathcal{M}_\ell)$ be a series of uncertain spaces for $\ell = 1, 2, \ldots$, then for arbitrary events Θ_ℓ chosen from Δ_ℓ for $\ell = 1, 2, \ldots$ respectively, $\mathcal{M}\left\{\prod_{\ell=1}^{\infty} \Theta_\ell\right\} = \bigwedge_{\ell=1}^{\infty} \mathcal{M}_\ell\{\Theta_\ell\}$.

Definition 2.2 *[14] A measurable function τ from an uncertainty space $(\Delta, \mathcal{A}, \mathcal{M})$ to the real numbers set is called an uncertain variable such that $\{\tau \in \mathcal{B}\}$ is an event, where $\mathcal{B}$ is any Borel set of real numbers.*

Definition 2.3 *[14] The expected value of an uncertain variable τ with a regular uncertainty distribution Ψ is defined by, $Ex[\tau] = \int_0^1 \Psi^{-1}(\alpha) d\alpha$.*

Table 1: A brief reviewed literature on the proposed work.

Paper	ND	Uncertainty	Obj.	Period	Pr.T	PT	PN	DP	SM
Afshar et al. [1]	Loc., PDVRP	Crisp	UD	Multi	HL	RI	Multi	√	CPLEX
Das et al. [4]	TLP	T2IF	C, EI, T	Single	OL	NRP	Single	×	FP, GCM
Entezaminia et al. [7]	TP	Crisp	C, EI	Multi	PD ,CL	RP	Multi	×	L-P Metric
Eydi and Alavi [8]	VRP	Crisp	C	Single	RL	RP	Single	×	SA
Gholizadeh et al. [10]	TP	RO	C	Multi	PD, CL	RP	Multi	×	MOGA
Moghaddam [22]	TP	Crisp	C, Q, LD, Risk	Single	SS, OA	RP	Multi	×	MCS + GP
Nayeri et al. [25].	TP	FRO	C, EI, SI	Single	PD, CL	RP	Multi	×	MCGP-UF
Rabbani et al. [27]	Loc.-Alloc., TP	FRO	C, EI, BQ	Multi	PD, CL	RP	Multi	√	AUGMECON
Roy et al. [29]	TP	Fuzzy-rough	C, T	Single	FL	NRP	Multi	×	FP, WGP, TOPSIS
Soleimani et al. [33].	PDVRP	Crisp	C,EI	Single	CL	RP	Multi	×	FP
Tofighi et al. [34]	Loc., TP	Fuzzy-stochastic	C, T, UD	Single	HL	RI	Multi	√	PSP, DE
Wang et al. [36]	-	Uncertain-random	C	Single	Inventory	NRP	Multi	×	Matlab
Zahiri et al. [37]	TP	Fuzzy-stochastic	C, SI, EI, R	Multi	PD, OL	NRP	Multi	×	HA
Zhalechian et al. [38]	Location-routing-inventory	Stochastic-possibilistic	C, EI, SI	Multi	CL	RP	Multi	×	Metaheuristic
Zhen et al. [39]	TP	Stochastic	C, EI	Single	CL	RP	Multi	×	LR
Proposed study	TP, PDVRP	Uncertain-random, RO	C, T, BQ, SI	Multi	PD, OL + CL, HL	RP, NRP	Multi	√	AWTM

ND: Network design; Obj.: Objective function; Pr.T: Problem type; PT: Product type; PN: Product number; SM: Solution method; Loc.-Aloc.: Location-Allocation; C: Cost/profit/loss; O: Others, T: Time, Q: Quality, LD: Late delivery, R: Resiliency, PD: Production-distribution, RI: Relief item, AUGMECON: Augmented ϵ-constraint, WGP: Weighted goal programming, LR: Lagrange relaxation, GCM: Global criterion method.

Definition 2.4 *[16] Let $(\Delta, \mathcal{A}, \mathcal{M})$ and $(\Upsilon, \mathcal{P}, Pr)$ be uncertain space and probability space respectively, then the chance measure of the uncertain-random event Λ in the chance space $(\Delta, \mathcal{A}, \mathcal{M}) \times (\Upsilon, \mathcal{P}, Pr) = (\Delta \times \Upsilon, \mathcal{A} \times \mathcal{P}, \mathcal{M} \times Pr)$ is defined by*

$$Ch[\Lambda] = \int_0^1 Pr\{\omega \in \Upsilon \mid \mathcal{M}\{\gamma \in \Delta \mid (\gamma, \omega) \in \Lambda\} \geqslant r\} dr.$$

Definition 2.5 *[16] A function ζ from the chance space $(\Delta, \mathcal{A}, \mathcal{M}) \times (\Upsilon, \mathcal{P}, Pr)$ to the real numbers set is called an uncertain-random variable such that $\{\zeta \in \mathcal{B}\}$ is an event in $\Delta \times \Upsilon$, where $\mathcal{B}$ is any Borel set of real numbers.*

Definition 2.6 *[16] Let $\tau^1, \tau^2, \ldots, \tau^S$ be uncertain variables, then a simple uncertain-random* *variable is defined by,* $\zeta = \begin{cases} \tau^1 \text{ with probability (w.p) } \rho^1, \\ \tau^2 \text{ with probability (w.p) } \rho^2, \\ \ldots\ldots \\ \tau^S \text{ with probability (w.p) } \rho^S, \end{cases}$

where $\sum_{h=1}^{S} \rho^h = 1$. *The above mentioned simple uncertain-random variable actually assumes* S *future scenarios with appearance probabilities* $\rho^1, \rho^2, \ldots, \rho^S$ *respectively. Then it can be re-defined as* $\zeta = \begin{cases} \tau^1 \text{ w.p } \rho^1 \text{ (scenario 1)}, \\ \tau^2 \text{ w.p } \rho^2 \text{ (scenario 2)}, \\ \ldots\ldots \\ \tau^S \text{ w.p } \rho^S \text{ (scenario } S\text{)}, \end{cases}$

with $\sum_{h=1}^{S} \rho^h = 1$.

Remark 2.1 *[16] The expected value of the uncertain-random variable illustrated in definition 2.6 is defined as* $E[\zeta] = \sum_{h=1}^{S} \rho^h Ex[\tau^h]$.

Definition 2.7 *[16] The chance distribution of an uncertain-random variable* ζ *is given by* $\Phi(x) = Ch\{\zeta \leqslant x\}$ *and* $1 - \Phi(x) = Ch\{\zeta > x\}$ *for any* $x \in \mathbb{R}$.

Definition 2.8 *[16] The chance distribution of the uncertain-random variable* ζ *defined in Definition 2.6 is given as* $\Phi(x) = \sum_{h=1}^{S} \rho^h \Psi^h(x)$, *where* $\Psi^h(x)$ *and* ρ^h *are the uncertainty distribution and occurrence probability of the uncertain variable* τ^h *under scenario* h *respectively.*

Definition 2.9 *[24] A trapezoidal intuitionistic fuzzy number (TrIFN)* $\widetilde{\mathcal{A}}^I$, *with the form,* $\widetilde{\mathcal{A}}^I = \left(f_1.f_2, f_3, f_4; f_1^{'}, f_2^{'}, f_3^{'}, f_4^{'}\right)$ *is an intuitionistic fuzzy number whose membership and non-membership functions are given as:*

$$\varphi_{\widetilde{\mathcal{A}}^I}(x) = \begin{cases} \dfrac{x - f_1}{f_2 - f_1}, & f_1 \leqslant x \leqslant f_2, \\ 1, & f_2 \leqslant x \leqslant f_3, \\ \dfrac{f_4 - x}{f_4 - f_3}, & f_3 \leqslant x \leqslant f_4, \\ 0, & \text{elsewhere}, \end{cases} \quad \text{and} \quad \psi_{\widetilde{\mathcal{A}}^I}(x) = \begin{cases} \dfrac{f_2^{'} - x}{f_2^{'} - f_1^{'}}, & f_1^{'} \leqslant x \leqslant f_2^{'}, \\ 0, & f_2^{'} \leqslant x \leqslant f_3^{'}, \\ \dfrac{x - f_3^{'}}{f_4^{'} - f_3^{'}}, & f_3^{'} \leqslant x \leqslant f_4^{'}, \\ 1, & \text{elsewhere}, \end{cases}$$

where $f_1^{'} \leqslant f_1 \leqslant f_2^{'} \leqslant f_2 \leqslant f_3 \leqslant f_3^{'} \leqslant f_4 \leqslant f_4^{'}, f_i$ *and* $f_i^{'} \in \mathbb{R}$ *for* $i = 1, 2, 3, 4$.

Definition 2.10 *[24]* (α, β)*-cut of a TrIFN* $\tilde{\mathcal{A}}^I$ *is defined as* $\widetilde{\mathcal{A}}^I_{(\alpha,\beta)} = \{x : \varphi_{\widetilde{\mathcal{A}}^I}(x) \geqslant \alpha$ *and* $\psi_{\widetilde{\mathcal{A}}^I}(x) \leqslant \beta, \alpha + \beta \leqslant 1, x \in X\}$.

3 Motivation for choosing mixed uncertainty

In real-life problems, usually parameters can be defined as random or uncertain. However, in complicated systems, randomness and uncertainty often appear simultaneously [36]. An example is set to explain why we consider such a mixed uncertainty. Suppose, by marketing experiences the demand of a particular type of medicine at any hospital usually will be 150 units with probability 0.25 in one scenario, 180 units with probability 0.35 in an other scenario and 170 units with probability 0.4 in another scenario. But, when an unpredictable or undesirable emergency situation occurs (like pandemic COVID-19), only previous experiences or data are not enough to describe the demand properly, then some experts' belief degrees are also needed along with historical data to figure out the demand. Suppose, two experts' opinion about the demand in first scenario are as: *(i) The demand will be in between 140 and 160 but not less than 140* and *(ii) The demand will be less than 160, but greater will be better,* respectively, also by previous experiences it is noted that the occurrence probability of this scenario will be 0.25. Therefore the demand of that scenario can be predicted by a linear uncertain variable $\mathcal{L}(140, 160)$ with the uncertainty distribution, given in Fig. 2 with probability 0.25; by similar process the demand of the other two scenarios can be predicted. Thus, the demand of that hospital will be estimated by a simple uncertain-random variable as: $\zeta_{dem} = \begin{cases} \mathcal{L}(140, 160) \text{ w.p } 0.25 \text{ (scenario 1)}, \\ \mathcal{L}(170, 190) \text{ w.p } 0.35 \text{ (scenario 2)}, \\ \mathcal{L}(160, 180) \text{ w.p } 0.4 \text{ (scenario 3)}. \end{cases}$

Proceeding with similar process other ill-known parameters associated with the proposed model can be estimated.

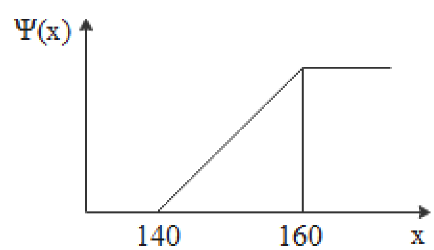


Fig. 2: Uncertainty distribution of the linear uncertain variable.

4 Problem description

In this section, we propose an MOMIP, which designs a two-stage integrated SOCLSC with multiple objectives, multiple products and multiple periods under uncertain-random environment consisting multiple hybrid production-distribution centers (hybrid production-recovery-distribution centers), multiple hybrid TCCs and multiple disposal centers (DCs) to supply products to multiple hospitals situated in COVID-19 affected areas. Two types of products, NRPs, which are produced at non-reusable product production-distribution center (NRPC), and RPs, which are produced and recovered at reusable product production-recovery-distribution center (RPRC), are considered. One TCC is installed at each affected area which is able to receive new products from NRPCs and RPRCs and transfers these to hospitals in forward flow, as well as to collect returned used RPs from hospitals, and after inspection and classification to send recoverable and scrapped RPs to RPRCs and DCs respectively in reverse flow. In first stage, shipping among NRPCs and TCCs (situated in various areas) is done through heterogeneous fleet of vehicles available at NRPCs, and shipping among RPRCs and TCCs (situated in various areas) and among TCCs and DCs is done through heterogeneous fleet of vehicles available at RPRCs for both forward and reverse flows, and in second stage, i.e., from TCCs to hospitals, each TCC distributes and collects products through their own available heterogeneous fleet of vehicles for both forward and reverse flows; also in second stage, vehicles simultaneously make delivery and pick-up at all hospitals by serving split demands. There are restrictions in capacities of facilities in both forward and reverse networks and also in vehicles' capacities by predefined amounts. The amount of demand at TCCs and hospitals may not be fulfilled in every period due to limited capacities of facilities and vehicles, shortage of raw materials, limited available working time etc., the unfulfilled demand in any period is considered as backlog amount in that period which has to be satisfied in the upcoming periods. Moreover, the backlog quantity is set upto a predetermined fraction of demand. Returned quantity of used RPs in any period at hospitals is assumed to be a fraction of previous period's delivered amount of RPs, also a predefined value is set as an average recovery and disposal ratio for returned RPs. At the end of each period remaining products are stocked as inventory levels, which are used as forwarding quantities for the next period. The objective of this planning is to find the optimal quantities of production, recovery and distribution between facilities as well as optimal routes of the vehicles such that the demand of all products at each hospital is satisfied at least upto a minimum level by optimizing economical (total cost), satisfactory (time and backlog amounts) and social aspects (employments).

In order to develop the real-life based SOCLSC model, the following assumptions are chosen:

- All facilities are set up from the beginning of the planning, and locations are fixed and predefined.
- NRPCs, RPRCs and TCCs are acted as hybrid facilities, i.e., those facilities can perform more than one activity.
- NRPs cannot be recovered or reused, so these are not collected from hospitals, and recovered RPs are redistributed as new products.
- Capacities of facilities are limited and known, also each TCC in each area is capable to distribute new products to the hospitals and collect used products from the hospitals.
- A TCC, which is located in an area does not deliver (collect) products to (from) other areas.
- Some parameters are treated as uncertain-random variables due to absence of sufficient information.
- Split deliveries are allowed at each hospital.

A notional outline of the proposed research work is delineated in Fig. 3.
In order to trace the model the following notations are used:
- *Sets*

I', I'', I	Sets of NRPCs, RPRCs and all production centers respectively, $I = I' \cup I''$,
J	Set of TCCs,
M	Set of DCs,
V_n	Set of vehicles available in NRPCs,
V_r	Set of vehicles available in RPRCs,
V_j	Set of vehicles available in j^{th} TCC for distribution,
P', P'', P	Sets of NRPs, RPs and all products respectively, $P = P' \cup P''$,
H_j	Set of hospitals covered by j^{th} TCC,
T	Set of periods $(t = 1, 2, \ldots, \mathcal{T})$.

- *Parameters*

ζ_{tc_v}	Uncertain random transportation cost of v^{th} vehicle for shipping per unit products per unit distance $v \in V_n \cup V_r$,
$\zeta_{etc_v}, \zeta_{atc_v}$	Uncertain random transportation cost of empty and additionally loaded v^{th} vehicle for shipping per unit products per unit distance $v \in V_j$,
d_{ij}	Distance between i^{th} and j^{th} node,
$\zeta_{pc^1_p}$	Uncertain random production cost for per unit p^{th} NRPs,
$\zeta_{pc^2_p}, \zeta_{rc_p}$	Uncertain random production and recovery cost respectively for per unit p^{th} RPs,

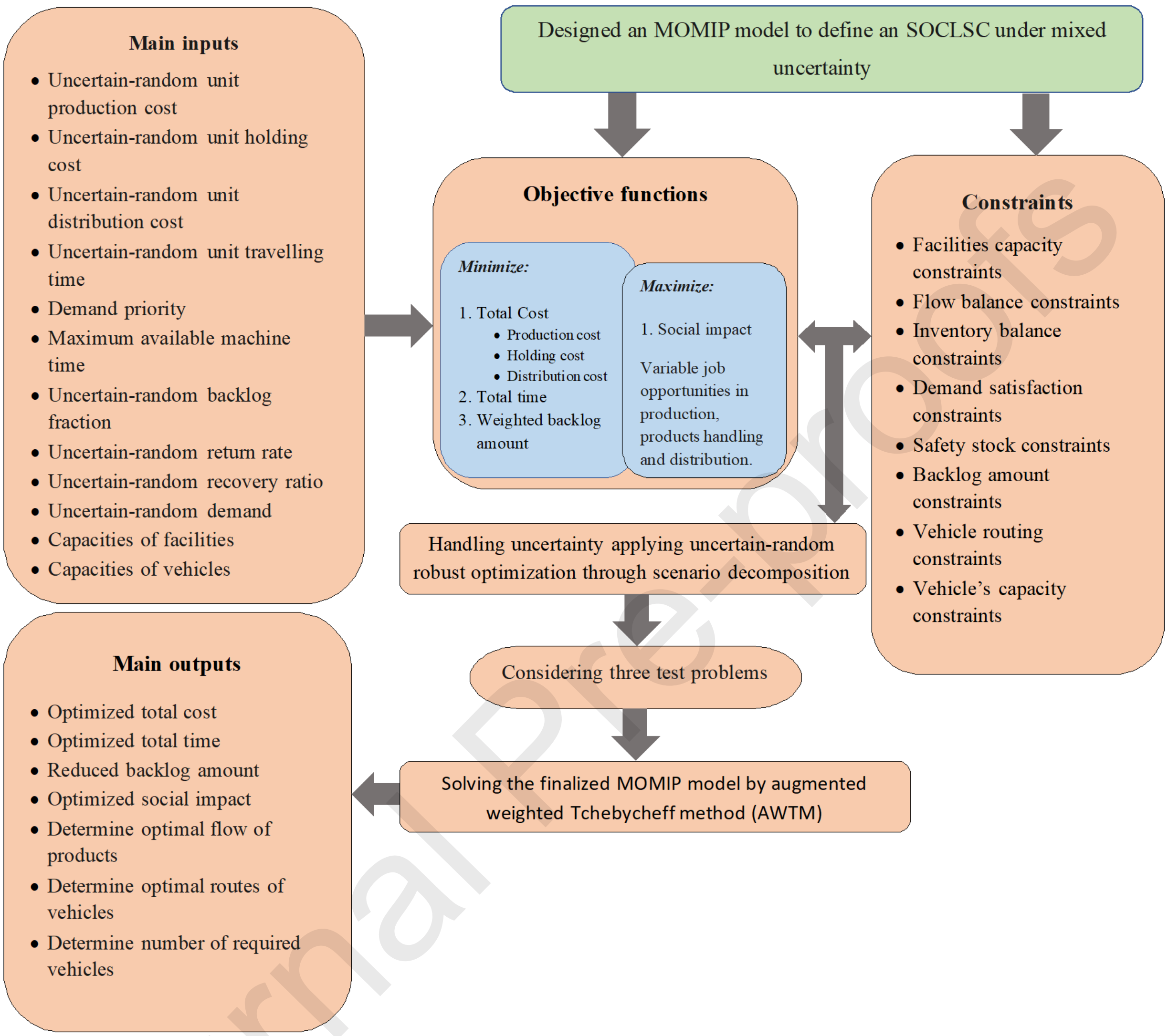


Fig. 3: A notional outline of the proposed research work.

$\zeta_{hc^1_{ip}}$	Uncertain random holding cost for per unit p^{th} NRPs in i^{th} NRPC,
$\zeta_{hc^2_{ip}}$	Uncertain random holding cost for per unit p^{th} RPs in i^{th} RPRC,
$\zeta_{hc^3_{ip}}$	Uncertain random holding cost for per unit p^{th} product in j^{th} TCC,
ζ_{t_v}	Uncertain random time required by fully loaded v^{th} vehicle for travelling per unit distance $v \in V_n \cup V_r$,
$\zeta_{et_v}, \zeta_{at_v}$	Uncertain random time required by empty and additionally loaded v^{th} vehicle for shipping per unit product per unit distance $v \in V_j$,
jv^t_f	Variable number of job opportunity created at facility $f \in I \cup J \cup M$ in period t,
$js^t_{nn'}$	Variable number of job opportunity created for shipping products from node n to node n' in period t $(n, n' \in I \cup J \cup M \cup H_j)$,

pr_j^t	Demand priority of j^{th} TCC in period t,
$\zeta_{dm_{jp}^t}$	Uncertain-random demand of p^{th} product at j^{th} TCC in period t,
cf_j^p	Capacity of j^{th} TCC for handling p^{th} product in forward flow,
ci_j^p	Storage capacity of j^{th} TCC for p^{th} product,
ζ_{θ_p}	Uncertain random recovery ratio of returned p^{th} RP,
m_{ip}^1	Machine time required to produce one unit p^{th} NRP at i^{th} NRPC,
m_{ip}^2, m_{ip}^3	Machine time required to produce and recover one unit p^{th} RP at i^{th} RPRC,
$m1_{i_{max}}^t$	Maximum machine time available at i^{th} NRPC in period t,
$m2_{i_{max}}^t$	Maximum machine time available at i^{th} RPRC in period t,
cr_i^p	Recovery capacity of i^{th} RPRC for recoverable p^{th} RP,
dr_m^p	Disposal capacity of m^{th} DC for scrapped p^{th} RP,
rr_j^p	Capacity of j^{th} TCC for handling returned p^{th} RP in reverse flow,
$s1_{ip}$	Capacity for storage at i^{th} NRPC,
$s2_{ip}$	Capacity for storage at i^{th} RPRC,
$\pi1_{pt}$	Maximum allowable fraction of demand of p^{th} product to be backlogged for first stage in period t,
$\pi2_{pt}$	Maximum allowable fraction of demand of p^{th} product to be backlogged for second stage in period t,
$\zeta_{dem_{pk}^t}$	Demand of k^{th} hospital for product p in period t,
c_v	Capacity of v^{th} vehicle available,
$\zeta_{\lambda_k^p}$	Uncertain random rate of return of used p^{th} RP at k^{th} hospital,
$\mathcal{N}$	Large number.

- *Decision variables*

X_{ip}^t	Amount of p^{th} NRP produced at i^{th} NRPC during period t,
Y_{ip}^t	Amount of p^{th} RP produced at i^{th} RPRC during period t,
Z_{ip}^t	Recovered amount of recoverable p^{th} RP at i^{th} RPRC during period t,
x_{ijv}^{pt}	Amount of p^{th} NRP shipped from i^{th} NRPC to j^{th} TCC by v^{th} vehicle in period t,
y_{ijv}^{pt}	Amount of p^{th} RP shipped from i^{th} RPRC to j^{th} TCC by v^{th} vehicle in period t,
z_{jiv}^{pt}	Amount of recoverable p^{th} RP transported from j^{th} TCC to i^{th} RPRC by v^{th} vehicle in period t,
w_{jmv}^{pt}	Amount of scrapped p^{th} RP transported from j^{th} TCC to m^{th} DC by v^{th} vehicle in period t,
$\delta_{k_1k_2v}^t$	Binary variable takes value "1" if journey occurs from node k_1 to node k_2 by vehicle v in period t otherwise "0",

$L^{pt}_{k_1 k_2 v}$	Amount of p^{th} product loaded in v^{th} vehicle while travelling from node k_1 to node k_2 in period t,
$F^{pt}_{k_1 k_2 v}$	Amount of returned p^{th} RP carried by v^{th} vehicle while travelling from node k_1 to node k_2 in period t,
$Q1^t_{ip}$	Inventory level of p^{th} NRP in i^{th} NRPC at the end of period t,
$Q2^t_{ip}$	Inventory level of p^{th} RP in i^{th} RPRC at the end of period t,
$Q3^t_{ip}$	Inventory level of p^{th} product at j^{th} TCC at the end of period t,
SL^t_{jp}	Safety stock level of p^{th} product at j^{th} TCC in period t,
$B1^t_{jp}$	Backlogged quantity of p^{th} product at j^{th} TCC in period t,
$B2^t_{kp}$	Backlogged quantity of p^{th} product at k^{th} hospital in period t,
A^t_{kvp}	Amount of p^{th} product delivered by v^{th} vehicle to k^{th} hospital in period t,
R^t_{kvp}	Amount of returned p^{th} RP collected by v^{th} vehicle from k^{th} hospital in period t,
U^t_{kv}	Dummy variable.

4.1 Determination of demand priority

In this subsection, we develop IFAHP to determine the priority of TCCs. To do this, we choose four attributes as follows:

$a^1_j(t)$ considers the total number of affected people in j^{th} affected area observed in period t. Higher number associated with an area indicates higher demand priority.

$a^2_j(t)$ represents the density of the population in j^{th} affected area in period t, which can be measured as $\left(\dfrac{\text{total alive people in area } j \text{ in period } t}{\text{total area } (j)}\right)$. For the contagious nature of the disease a higher population density infers to higher demand priority.

$a^3_j(t)$ defines the ratio of aged population (age $\geqslant$ 45 years) to the total number of affected people in j^{th} affected area in period t. Higher aged peoples' ratio for an area j indicates higher demand priority.

$a^4_j(t)$ calculates the percentage of survived and dead peoples in a period t in j^{th} affected area. Higher of this percentage implies lower demand priority.

It is assumed that all affected peoples are admitted to the hospitals.

Thereafter the method takes place through the following steps:

Step 1: For a given affected area j, all four attributes are measured in a certain period as the linguistic terms, "Very High (VH)", "High (H)", "Medium (M)", "Low (L)" and "Very Low (VL)" using the logic rules, which are given bellow:

$$\varphi(a_j^l(t)) = \begin{cases} VH, & \text{if } a_j^l(t) \geqslant 0.8\ a_{\max}^l(t), \\ H, & \text{if } 0.6\ a_{\max}^l(t) \leqslant a_j^l(t) < 0.8\ a_{\max}^l(t), \\ M, & \text{if } 0.4\ a_{\max}^l(t) \leqslant a_j^l(t) < 0.6\ a_{\max}^l(t), \\ L, & \text{if } 0.2\ a_{\max}^l(t) \leqslant a_j^l(t) < 0.4\ a_{\max}^l(t), \\ VL, & \text{if } a_j^l(t) < 0.2\ a_{\max}^l(t), \end{cases} \qquad \forall\ j \in J, l = 1,2,3,4, \forall\ t \in T$$

where $a_{\max}^l$ is the maximum value of $a_j^l,\ j \in J$.

Step 2: Therefore to represent the measured attributes, TrIFNs corresponding to the linguistic terms are shown in Table 2.

Table 2: Corresponding TrIFNs of linguistic terms.

Linguistic term	TrIFN
Very High (VH)	(8, 9, 9.5, 10; 7, 9, 9.5, 10)
High (H)	(7, 8, 8.5, 9; 6, 8, 8.5, 9.5)
Medium (M)	(5, 6, 6.5, 7; 4, 6, 6.5, 7)
Low (L)	(2, 2.5, 3, 3.5; 1, 2.5, 3, 4)
Very Low (VL)	(0.5, 1, 1.5, 2; 0, 1, 1.5, 2)

Step 3: Let there are M affected areas. Now construct an $M \times 4$ judgement matrix based on the representation in Step 2 as:

$$\begin{bmatrix} \widetilde{A}_{11}^I(t) & \widetilde{A}_{12}^I(t) & \widetilde{A}_{13}^I(t) & \widetilde{A}_{14}^I(t) \\ \widetilde{A}_{21}^I(t) & \widetilde{A}_{22}^I(t) & \widetilde{A}_{23}^I(t) & \widetilde{A}_{24}^I(t) \\ \cdots & \cdots & \cdots & \cdots \\ \widetilde{A}_{M1}^I(t) & \widetilde{A}_{M2}^I(t) & \widetilde{A}_{M3}^I(t) & \widetilde{A}_{M4}^I(t) \end{bmatrix}$$

where $\widetilde{A}_{jl}^I(t) = (u_{jl}^1, u_{jl}^2, u_{jl}^3, u_{jl}^4; u_{jl}^{1'}, u_{jl}^{2'}, u_{jl}^{3'}, u_{jl}^{4'})$ is the l^{th} attribute of j^{th} area, $\forall\ j = 1,2,\ldots,M$, $\forall\ l = 1,2,3,4, \forall\ t \in T$.

Step 4: Construct normalised judgement matrix as follows:

$$\begin{bmatrix} \widetilde{N}_{11}^I(t) & \widetilde{N}_{12}^I(t) & \widetilde{N}_{13}^I(t) & \widetilde{N}_{14}^I(t) \\ \widetilde{N}_{21}^I(t) & \widetilde{N}_{22}^I(t) & \widetilde{N}_{23}^I(t) & \widetilde{N}_{24}^I(t) \\ \cdots & \cdots & \cdots & \cdots \\ \widetilde{N}_{M1}^I(t) & \widetilde{N}_{M2}^I(t) & \widetilde{N}_{M3}^I(t) & \widetilde{N}_{M4}^I(t) \end{bmatrix}$$

where $\widetilde{N}_{jl}^I(t) = \left(\frac{u_{jl}^1}{u_l^*}, \frac{u_{jl}^2}{u_l^*}, \frac{u_{jl}^3}{u_l^*}, \frac{u_{jl}^4}{u_l^*}; \frac{u_{jl}^{1'}}{u_l^*}, \frac{u_{jl}^{2'}}{u_l^*}, \frac{u_{jl}^{3'}}{u_l^*}, \frac{u_{jl}^{4'}}{u_l^*}\right), \forall\ j = 1,2,\ldots,M, \forall\ l = 1,2,3, \forall\ t \in T$ (favourable attribute) and $\widetilde{N}_{jl}^I(t) = \left(\frac{\overline{u}_l}{u_{jl}^4}, \frac{\overline{u}_l}{u_{jl}^3}, \frac{\overline{u}_l}{u_{jl}^2}, \frac{\overline{u}_l}{u_{jl}^1}; \frac{\overline{u}_l}{u_{jl}^{4'}}, \frac{\overline{u}_l}{u_{jl}^{3'}}, \frac{\overline{u}_l}{u_{jl}^{2'}}, \frac{\overline{u}_l}{u_{jl}^{1'}}\right), \forall\ j = 1,2,\ldots,M$,

$l=4, \forall\ t \in T$ (unfavourable attribute), where $u_l^* = \max_{j=1,2,\ldots,M}\left(u_{jl}^{4'}\right), \forall\ l=1,2,3; \overline{u}_l = \min_{j=1,2,\ldots,M}\left(u_{jl}^{1'}\right), l=4$.

Step 5: Let the weights corresponding to four attributes are w_1, w_2, w_3, w_4 respectively. Then the formulated weighted (α,β)-cut normalised judgement matrix is as follows:

$$\begin{bmatrix} w_1\left[r_{11L}^{(\alpha,\beta)}(t), r_{11R}^{(\alpha,\beta)}(t)\right] & w_2\left[r_{12L}^{(\alpha,\beta)}(t), r_{12R}^{(\alpha,\beta)}(t)\right] & w_3\left[r_{13L}^{(\alpha,\beta)}(t), r_{13R}^{(\alpha,\beta)}(t)\right] & w_4\left[r_{14L}^{(\alpha,\beta)}(t), r_{14R}^{(\alpha,\beta)}(t)\right] \\ w_1\left[r_{21L}^{(\alpha,\beta)}(t), r_{21R}^{(\alpha,\beta)}(t)\right] & w_2\left[r_{22L}^{(\alpha,\beta)}(t), r_{22R}^{(\alpha,\beta)}(t)\right] & w_3\left[r_{23L}^{(\alpha,\beta)}(t), r_{23R}^{(\alpha,\beta)}(t)\right] & w_4\left[r_{24L}^{(\alpha,\beta)}(t), r_{24R}^{(\alpha,\beta)}(t)\right] \\ \cdots & \cdots & \cdots & \cdots \\ w_1\left[r_{M1L}^{(\alpha,\beta)}(t), r_{M1R}^{(\alpha,\beta)}(t)\right] & w_2\left[r_{M2L}^{(\alpha,\beta)}(t), r_{M2R}^{(\alpha,\beta)}(t)\right] & w_3\left[r_{M3L}^{(\alpha,\beta)}(t), r_{M3R}^{(\alpha,\beta)}(t)\right] & w_4\left[r_{M4L}^{(\alpha,\beta)}(t), r_{M4R}^{(\alpha,\beta)}\right](t) \end{bmatrix}$$

where $\left[r_{jlL}^{(\alpha,\beta)}(t), r_{jlR}^{(\alpha,\beta)}(t)\right]$ is the (α,β)-cut set of the TrIFN $\widetilde{N}_{jl}^I(t), \forall\ j=1,2,\ldots,M; l=1,2,3,4; \forall\ t \in T$.

Step 6: Now evaluate the precise judgement and frequency matrix respectively as follows:

$$\begin{bmatrix} p_{11}^\lambda(t) & p_{12}^\lambda(t) & p_{13}^\lambda(t) & p_{14}^\lambda(t) \\ p_{21}^\lambda(t) & p_{22}^\lambda(t) & p_{23}^\lambda(t) & p_{24}^\lambda(t) \\ \cdots & \cdots & \cdots & \cdots \\ p_{M1}^\lambda(t) & p_{M2}^\lambda(t) & p_{M3}^\lambda(t) & p_{M4}^\lambda(t) \end{bmatrix} \text{ and } \begin{bmatrix} f_{11}(t) & f_{12}(t) & f_{13}(t) & f_{14}(t) \\ f_{21}(t) & f_{22}(t) & f_{23}(t) & f_{24}(t) \\ \cdots & \cdots & \cdots & \cdots \\ f_{M1}(t) & f_{M2}(t) & f_{M3}(t) & f_{M4}(t) \end{bmatrix}$$

where $p_{jl}^\lambda(t) = w_l\left[(1-\lambda)r_{jlL}^{(\alpha,\beta)}(t) + \lambda r_{jlR}^{(\alpha,\beta)}(t)\right], \forall\ j=1,2,\ldots,M, l=1,2,3,4, \forall\ t \in T$ and $0 \leqslant \lambda \leqslant 1$; and $f_{jl}(t) = \dfrac{p_{jl}^\lambda(t)}{\sum_{l=1}^4 p_{jl}^\lambda(t)}, \forall\ j=1,2,\ldots,M, \forall\ l=1,2,3,4$.

Step 7: Then the corresponding entropy value and entropy weight of j^{th} TCC are $E_j(t) = -\sum_{l=1}^{4} f_{jl}(t)\log(f_{jl}(t))$ and $\mathrm{pr}_j^t = \dfrac{E_j(t)}{\sum_{j=1}^M E_j(t)}, \forall\ j=1,2,\ldots,M, \forall\ t \in T$ respectively.

4.2 Model identification

This section delivers an MOMIP model under mixed uncertainty, which is consisted of four objective functions and the necessary constraints, to describe the proposed SOCLSC.

4.2.1 Objective functions

Production and recovery cost:

$$\mathrm{PRC} = \sum_{i \in I'}\sum_{p \in P'}\sum_{t \in T} \zeta_{pc_p^1} X_{ip}^t + \sum_{i \in I''}\sum_{p \in P''}\sum_{t \in T}\left[\zeta_{pc_p^2} Y_{ip}^t + \zeta_{rc_p} Z_{ip}^t\right].$$

Distribution cost:

$$\text{DIC} = \sum_{j\in J}\sum_{t\in T}\left(\sum_{i\in I'}\sum_{v\in V_n}\sum_{p\in P'}\zeta_{tc_v}x^{pt}_{ijv}d_{ij} + \sum_{i\in I''}\sum_{v\in V_r}\sum_{p\in P''}\zeta_{tc_v}y^{pt}_{ijv}d_{ij}\right) +$$
$$\sum_{j\in J}\sum_{v\in V_r}\sum_{p\in P''}\sum_{t\in T}\left(\sum_{i\in I''}\zeta_{tc_v}z^{pt}_{jiv}d_{ji} + \sum_{m\in M}\zeta_{tc_v}w^{pt}_{jmv}d_{jm}\right) +$$
$$\sum_{j\in J}\sum_{k_1\in H_j}\sum_{k_2\in H_j}\sum_{v\in V_j}\sum_{t\in T}\left[\zeta_{etc_v}\delta^t_{k_1k_2v} + \zeta_{atc_v}\left(\sum_{p\in P}L^{pt}_{k_1k_2v} + \sum_{p\in P''}F^{pt}_{k_1k_2v}\right)\right]d_{k_1k_2}.$$

Holding cost:

$$\text{HC} = \sum_{i\in I'}\sum_{p\in P'}\sum_{t\in T}\zeta_{hc^1_{ip}}Q1^t_{ip} + \sum_{i\in I''}\sum_{p\in P''}\sum_{t\in T}\zeta_{hc^2_{ip}}Q2^t_{ip} + \sum_{j\in J}\sum_{p\in P}\sum_{t\in T}\zeta_{hc^3_{jp}}Q3^t_{jp}.$$

$$\text{minimize TC} = \text{PRC} + \text{DIC} + \text{HC}. \tag{4.1}$$

Total cost (TC) of this planning is minimized by objective function (4.1) which consists of production and recovery cost (PRC) at NRPCs and RPRCs, distribution cost (DIC) of forward and reverse flows and holding cost of products (HC) at production centers and TCCs.

Total transportation time:

$$\text{minimize}\sum_{j\in J}\sum_{t\in T}\left(\sum_{i\in I'}\sum_{v\in V_n}\sum_{p\in P'}\zeta_{t_v}\left(x^{pt}_{ijv}/c_v\right)d_{ij} + \sum_{i\in I''}\sum_{v\in V_r}\sum_{p\in P''}\zeta_{t_v}\left(y^{pt}_{ijv}/c_v\right)d_{ij}\right) +$$
$$\sum_{j\in J}\sum_{t\in T}\sum_{v\in V_r}\sum_{p\in P''}\left(\sum_{i\in I''}\zeta_{t_v}\left(z^{pt}_{jiv}/c_v\right)d_{ji} + \sum_{m\in M}\zeta_{t_v}\left(w^{pt}_{jmv}/c_v\right)d_{jm}\right) +$$
$$\sum_{j\in J}\sum_{k_1\in H_j}\sum_{k_2\in H_j}\sum_{v\in V_j}\sum_{t\in T}\left[\zeta_{et_v}\delta^t_{k_1k_2v} + \zeta_{at_v}\left(\sum_{p\in P}L^{pt}_{k_1k_2v} + \sum_{p\in P''}F^{pt}_{k_1k_2v}\right)\right]d_{k_1k_2}. \tag{4.2}$$

Objective function (4.2) minimizes total distribution time of forward and reverse flow.

Total backlog amount:

$$\text{minimize}\sum_{j\in J}\sum_{p\in P}\sum_{t\in T}\text{pr}_j(t)B^1_{jp}(t) + \sum_{k\in H_j}\sum_{p\in P}\sum_{t\in T}B^2_{kp}(t). \tag{4.3}$$

Objective function (4.3) is considered to enhance satisfaction of TCCs and hospitals through minimizing total backlogged quantities.

Total created job opportunity:

$$\text{maximize JOB} = \text{PRJ} + \text{HJ} + \text{DJ}. \tag{4.4}$$

$$\text{PRJ} = \sum_{i\in I'}\sum_{t\in T} jv_i^t \left(m_{ip}^1 X_{ip}^t\right)/m1_{i_{max}}^t + \sum_{i\in I''}\sum_{t\in T} jv_i^t \left(m_{ip}^2 Y_{ip}^t + m_{ip}^3 Z_{ip}^t\right)/m2_{i_{max}}^t.$$

$$\text{HJ} = \sum_{j\in J}\sum_{t\in T} jv_j^t \left(\sum_{i\in I'}\sum_{v\in V_n}\sum_{p\in P'} x_{ijv}^{pt} + \sum_{i\in I''}\sum_{v\in V_r}\sum_{p\in P''} y_{ijv}^{pt}\right)/cf_j^p +$$
$$\sum_{t\in T}\left[\sum_{i\in I''} jv_i^t \left(\sum_{j\in J}\sum_{v\in V_r}\sum_{p\in P''} z_{jiv}^{pt}\right)/cr_i^{p'} + \sum_{m\in M} jv_m^t \left(\sum_{j\in J}\sum_{v\in V_r}\sum_{p\in P''} w_{jmv}^{pt}\right)/dc_m^p\right] +$$
$$\sum_{j\in J}\sum_{t\in T} jv_j^t \left(\sum_{k\in H_j}\sum_{v\in V_j}\sum_{p\in P''} F_{kjv}^{pt}\right)/rr_j^p.$$

$$\text{DJ} = \sum_{i\in I'}\sum_{j\in J}\sum_{v\in V_n}\sum_{p\in P'}\sum_{t\in T} js_{ij}^t x_{ijv}^{pt}/c_v + \sum_{i\in I''}\sum_{j\in J}\sum_{v\in V_r}\sum_{p\in P''}\sum_{t\in T}\left(js_{ij}^t y_{ijv}^{pt}/c_v + js_{ji}^t z_{jiv}^{pt}/c_v\right) +$$
$$\sum_{j\in J}\sum_{m\in M}\sum_{v\in V_r}\sum_{p\in P''}\sum_{t\in T} js_{jm}^t w_{jmv}^{pt}/c_v + \sum_{j\in J}\sum_{k\in H_j}\sum_{v\in V_j}\sum_{t\in T} js_{jk}^t \left(\sum_{p\in P} A_{kvp}^t + \sum_{p\in P'} R_{kvp}^t\right)/c_v.$$

Objective function (4.4) maximizes total job opportunities consisting of production and recovery job (PRJ), created during production and recovery in production (production-recovery) centers, handling job (HJ), for handling products in different facilities, and distribution job (DJ), created during distributing products among facilities.

4.2.2 Constraints

$$\sum_{p\in P'} m_{ip}^1 X_{ip}^t \leqslant m1_{i_{max}}^t, \quad \forall\, i \in I', \forall\, t \in T \tag{4.5}$$

$$\sum_{p\in P''} \left(m_{ip}^2 Y_{ip}^t + m_{ip}^3 Z_{ip}^t\right) \leqslant m2_{i_{max}}^t, \quad \forall\, i \in I'', \forall\, t \in T \tag{4.6}$$

$$Z_{ip}^t = \sum_{j\in J}\sum_{v\in V_r} z_{jiv}^{pt}, \quad \forall\, i \in I'', \forall\, p \in P'', \forall\, t \in T \tag{4.7}$$

Constraints (4.5) and (4.6) are included to limit the produced quantity at NRPCs, and produced and recovered quantity at RPRCs by their maximum capacity respectively in terms of machine time during a period. Constraints (4.7) define the recovered quantities at RPRCs during a period.

$$Q1_{ip}^{t} = Q1_{ip}^{t-1} + X_{ip}^{t} - \sum_{j \in J} \sum_{v \in V_n} x_{ijv}^{pt}, \quad \forall\, i \in I', \forall\, p \in P', \forall\, t \in T \tag{4.8}$$

$$Q2_{ip}^{t} = Q2_{ip}^{t-1} + \left(Y_{ip}^{t} + Z_{ip}^{t}\right) - \sum_{j \in J} \sum_{v \in V_r} y_{ijv}^{pt}, \quad \forall\, i \in I'', \forall\, p \in P'', \forall\, t \in T \tag{4.9}$$

$$Q3_{jp}^{t} = Q3_{jp}^{t-1} + \sum_{i \in I'} \sum_{v \in V_n} x_{ijv}^{pt} - \sum_{k \in H_j} \sum_{v \in V_j} A_{kvp}^{t}, \quad \forall\, j \in J, \forall\, p \in P', \forall\, t \in T \tag{4.10}$$

$$Q3_{jp}^{t} = Q3_{jp}^{t-1} + \sum_{i \in I''} \sum_{v \in V_r} y_{ijv}^{pt} - \sum_{k \in H_j} \sum_{v \in V_j} A_{kvp}^{t}, \quad \forall\, j \in J, \forall\, p \in P'', \forall\, t \in T \tag{4.11}$$

$$SL_{jp}^{t} = \mathrm{pr}_j^{t} \sum_{i \in I'} \sum_{v \in V_n} x_{ijv}^{pt}, \quad \forall\, j \in J, \forall\, p \in P', \forall\, t \in T \tag{4.12}$$

$$SL_{jp}^{t} = \mathrm{pr}_j^{t} \sum_{i \in I''} \sum_{v \in V_r} y_{ijv}^{pt}, \quad \forall\, j \in J, \forall\, p \in P'', \forall\, t \in T \tag{4.13}$$

$$Q3_{jp}^{t} \geqslant SL_{jp}^{t}, \quad \forall\, j \in J, \forall\, p \in P, \forall\, t \in T \tag{4.14}$$

$$\sum_{i \in I'} \sum_{v \in V_n} x_{ijv}^{pt} + B1_{kp}^{t} - B1_{kp}^{t-1} + Q3_{jp}^{t-1} \geqslant \zeta_{dm_{jp}^{t}}, \quad \forall\, j \in J, \forall p \in P', \forall\, t \in T \tag{4.15}$$

$$\sum_{i \in I''} \sum_{v \in V_r} y_{ijv}^{pt} + B1_{kp}^{t} - B1_{kp}^{t-1} + Q3_{jp}^{t-1} \geqslant \zeta_{dm_{jp}^{t}}, \quad \forall\, j \in J, \forall p \in P'', \forall\, t \in T \tag{4.16}$$

$$\sum_{v \in V_j} A_{kvp}^{t} + B2_{kp}^{t} - B2_{kp}^{t-1} \geqslant \zeta_{dem_{kp}^{t}}, \quad \forall\, j \in J, \forall\, k \in H_j, \forall\, p \in P, \forall\, t \in T \tag{4.17}$$

$$B2_{kp}^{t} = 0, \quad t = \mathcal{T}, \forall\, j \in J, \forall\, k \in H_j, \forall\, p \in P \tag{4.18}$$

The relationships among inventory levels at the start and end of a period, production and recovery amounts and transported quantities in that period at each NRPC and RPRC are defined by constraints (4.8) and (4.9) respectively. Constraints (4.10) and (4.11) relate inventory level at the start and end of a period with backlogged, received and distributed quantity at each TCC in that period for NRP and RP respectively. The safety stock level of NRP and RP at each TCC in each period are calculated in constraints (4.12) and (4.13) respectively. It is worthy to note that, the safety stocks at TCCs are considered to be variable and depended on the received amounts and demand priorities. Inventory levels of each product should be higher than safety stock at TCCs for emergency needs, which are defined by constraints (4.14). Constraints (4.15), (4.16) and (4.17) state that the demand of each product in each TCC and each hospital must be satisfied considering backlog amounts. Also, the delivery amounts to TCCs in any period are reduced by previous period's inventory stocks. In addition, constraints (4.18) imply that the backlog amount should be equal to zero in the last time period in each hospital.

$$\sum_{i \in I''} \sum_{v \in V_r} z_{jiv}^{pt} = \zeta_{\theta_p} \sum_{v \in V_j} \sum_{k \in H_j} F_{kjv}^{pt}, \quad \forall\, j \in J, \forall\, p \in P'', \forall\, t \in T \tag{4.19}$$

$$\sum_{m \in M} \sum_{v \in V_r} w_{jmv}^{pt} = \left(1 - \zeta_{\theta_p}\right) \sum_{v \in V_j} \sum_{k \in H_j} F_{kjv}^{pt}, \quad \forall\, j \in J, \forall\, p \in P'', \forall\, t \in T \tag{4.20}$$

$$\sum_{v \in V_j} R_{kvp}^{t} = \zeta_{\lambda_k^p} \sum_{v \in V_j} A_{kvp}^{t-1}, \quad \forall\, j \in J, \forall\, k \in H_j, \forall\, p \in P'', \forall\, t \in T \tag{4.21}$$

$$\sum_{k_1 \in \{j\} \cup H_j} L_{k_1 k_2 v}^{pt} - \sum_{k_3 \in H_j} L_{k_2 k_3 v}^{pt} = A_{k_2 v p}^{t}, \quad \forall\, j \in J, \forall\, k_2 \in H_j, \forall\, v \in V_j, \forall\, p \in P, \forall\, t \in T \tag{4.22}$$

$$\sum_{k_2 \in \{j\} \cup H_j} F_{k_1 k_2 v}^{pt} - \sum_{k_3 \in H_j} F_{k_3 k_1 v}^{pt} = R_{k_1 v p}^{t}, \quad \forall\, j \in J, \forall\, k_1 \in H_j, \forall\, v \in V_j, \forall\, p \in P'', \forall\, t \in T \tag{4.23}$$

Constraints (4.19) – (4.23) are included to maintain the flow balance among facilities in forward and reverse flows. Amount of recoverable and scrapped RPs are calculated by constraints (4.19) and (4.20). The amount of used RPs those are returned in a certain period are calculated by constraints (4.21). Constraints (4.22) and (4.23) compute the amount of new products delivered to each hospital and the amount of returned RPs collected from each hospital respectively by a vehicle (if visits) in a period.

$$\sum_{i \in I'} \sum_{v \in V_n} x_{ijv}^{pt} \leqslant cf_j^p, \quad \forall\, j \in J, \forall\, p \in P', \forall\, t \in T \tag{4.24}$$

$$\sum_{i \in I''} \sum_{v \in V_r} y_{ijv}^{pt} \leqslant cf_j^p, \quad \forall\, j \in J, \forall\, p \in P'', \forall\, t \in T \tag{4.25}$$

$$\sum_{j \in J} \sum_{v \in V_r} z_{jiv}^{pt} \leqslant cr_i^p, \quad \forall\, i \in I'', \forall\, p \in P'', \forall\, t \in T \tag{4.26}$$

$$\sum_{j \in J} \sum_{v \in V_r} w_{jmv}^{pt} \leqslant dr_m^p, \quad \forall\, m \in M, \forall\, p \in P'', \forall\, t \in T \tag{4.27}$$

$$\sum_{k \in H_j} \sum_{v \in V_j} F_{kjv}^{pt} \leqslant rr_j^p, \quad \forall\, j \in J, \forall\, p \in P'', \forall\, t \in T \tag{4.28}$$

$$\sum_{t \in T} Q1_{ip}^{t} \leqslant s1_{ip}, \quad \forall\, i \in I', \forall\, p \in P' \tag{4.29}$$

$$\sum_{t \in T} Q2_{ip}^{t} \leqslant s2_{ip}, \quad \forall\, i \in I'', \forall\, p \in P'' \tag{4.30}$$

$$\sum_{t \in T} Q3_{jp}^{t} \leqslant ci_j^p, \quad \forall\, j \in J, \forall\, p \in P \tag{4.31}$$

Constraints (4.24) and (4.25) ensure that flows entering to each TCC in forward flow do not exceed its product handling capacity. Recovery capacity at each RPRC, disposal capacity at each DC and handling returned RPs capacity at each TCC are maintained by constraints

(4.26), (4.27) and (4.28) respectively. Constraints (4.29), (4.30) and (4.31) define the inventory holding capacity at each NRPC, RPRC and TCC respectively.

$$B1^t_{jp} \leqslant \pi 1^t_p \zeta_{dm^t_{jp}}, \quad \forall\ j \in J, \forall\ p \in P, \forall\ t \in T \tag{4.32}$$

$$B2^t_{kp} \leqslant \pi 2^t_p \zeta_{dem^t_{kp}}, \quad \forall\ j \in J, \forall\ k \in H_j, \forall\ p \in P, \forall\ t \in T \tag{4.33}$$

Constraints (4.32) and (4.33) restrict the backlogged quantity at each TCC and each hospital in each period respectively.

$$\sum_{k_1 \in \{j\} \cup H_j} \sum_{v \in V_j} \delta^t_{k_1 k_2 v} \geqslant 1, \quad \forall\ j \in J, \forall\ k_2 \in \{j\} \cup H_j, \forall\ t \in T \tag{4.34}$$

$$\sum_{k \in H_j} \delta^t_{jkv} \leqslant 1, \quad \forall\ j \in J, \forall\ v \in V_j, \forall\ t \in T \tag{4.35}$$

$$\sum_{k_1 \in \{j\} \cup H_j} \delta^t_{k_1 k_2 v} - \sum_{k_3 \in \{j\} \cup H_j} \delta^t_{k_2 k_3 v} = 0, \quad \forall\ j \in J, \forall\ k_2 \in \{j\} \cup H_j, \forall\ v \in V_j, \forall\ t \in T \tag{4.36}$$

$$U^t_{k_1 v} + \delta^t_{k_1 k_2 v} \leqslant U^t_{k_2 v} + \mathcal{N}(1 - \delta^t_{k_1 k_2 v}), \quad \forall\ j \in J, \forall\ k_1, k_2 \in H_j, \forall v \in V_j, \forall\ t \in T \tag{4.37}$$

Equations (4.34) – (4.37) are the constraints related to PDVRP. Constraints (4.34) ensure that each node is accessed at least once in each period. Constraints (4.35) state that vehicles go out for delivery if necessary, unless not. Constraints (4.36) impose that the number of going-in and going-out vehicles are same at each node in each period. Constraints (4.37) are put to eliminate sub-tours.

$$\sum_{i \in I'} \sum_{j \in J} \sum_{p \in P'} x^{pt}_{ijv} \leqslant c_v, \quad \forall\ v \in V_n, \forall\ t \in T \tag{4.38}$$

$$\sum_{i \in I''} \sum_{j \in J} \sum_{p \in P''} y^{pt}_{ijv} \leqslant c_v, \quad \forall\ v \in V_r, \forall\ t \in T \tag{4.39}$$

$$\sum_{j \in J} \sum_{i \in I''} \sum_{p \in P''} z^{pt}_{jiv} \leqslant c_v, \quad \forall\ v \in V_r, \forall\ t \in T \tag{4.40}$$

$$\sum_{j \in J} \sum_{m \in M} \sum_{p \in P''} w^{pt}_{jmv} \leqslant c_v, \quad \forall\ v \in V_r, \forall\ t \in T \tag{4.41}$$

$$\sum_{k \in H_j} \left(\sum_{p \in P} A^t_{kvp} + \sum_{p \in P''} R^t_{kvp} \right) \leqslant c_v, \quad \forall\ j \in J, \forall\ v \in V_j, \forall\ t \in T \tag{4.42}$$

$$\sum_{p \in P} L^{pt}_{k_1 k_2 v} + \sum_{p \in P''} F^{pt}_{k_1 k_2 v} \leqslant c_v \delta^t_{k_1 k_2 v}, \quad \forall\ j \in J, \forall\ k_1, k_2 \in \{j\} \cup H_j, \forall\ v \in V_j, \forall\ t \in T \tag{4.43}$$

Constraints (4.38) – (4.43) are inserted to preserve vehicle capacity in forward and reverse flows in each period.

$$Q1^0_{ip} = 0, \quad \forall\ i \in I', \forall\ p \in P' \tag{4.44}$$

$$Q2^0_{ip} = 0, \quad \forall\ i \in I'', \forall\ p \in P'' \tag{4.45}$$

$$Q3^0_{jp} = B1^0_{jp} = B2^0_{kp} = 0, \quad \forall\ j \in J, \forall\ p \in P, \forall\ k \in H_j \tag{4.46}$$

$$\delta^t_{k_1 k_2 v} = \{0, 1\}, \quad \forall\ j \in J, \forall\ k_1, k_2 \in \{j\} \cup H_j, \forall\ v \in V_j, \forall\ t \in T \tag{4.47}$$

and all other variables are non-negative for their respective indices.

5 Uncertain-random robust optimization

Instead of solving the proposed model by traditional methods such as uncertain-random programming ([36]) or uncertain-random goal programming ([26]), we suggest a RO approach in this section to deal with uncertainty of the model. RO technique is basically applied by considering various uncertainty sets or by formulating min-max regret model or by decomposing scenarios ([10], [21]). The third approach would be appropriate for a problem in simple uncertain-random environment, as a simple uncertain-random variable is composed with different uncertain variable(s) under different scenario(s) with probability (probabilities) (see Definition 2.6). Therefore, by decomposing scenarios of the uncertain-random parameters, and using expected values and chance distributions, we develop a robust counterpart model of the proposed model as follows:

Model 1

$$\text{minimize } Z_1 = \sum_{h=1}^{S} \rho^h Ex[\mathcal{Z}^h_1] + a_1 \sum_{h=1}^{S} \rho^h \left\{ \left(Ex[\mathcal{Z}^h_1] - \sum_{h=1}^{S} \rho^h Ex[\mathcal{Z}^h_1] \right) + 2\upsilon^h_1 \right\}$$

$$\text{minimize } Z_2 = \sum_{h=1}^{S} \rho^h Ex[\mathcal{Z}^h_2] + a_2 \sum_{h=1}^{S} \rho^h \left\{ \left(Ex[\mathcal{Z}^h_2] - \sum_{h=1}^{S} \rho^h Ex[\mathcal{Z}^h_2] \right) + 2\upsilon^h_2 \right\}$$

$$\text{minimize } Z_3 = \sum_{j\in J} \sum_{p\in P} \sum_{t\in T} \mathrm{pr}^t_j B1^t_{jp} + \sum_{k\in H_j} \sum_{p\in P} \sum_{t\in T} B2^t_{kp}$$

$$\text{minimize } Z_4 = -\ \mathrm{JOB}$$

$$\text{subject to} \qquad Ex[\mathcal{Z}^h_1] - \sum_{h=1}^{S} \rho^h Ex[\mathcal{Z}^h_1] + \upsilon^h_1 \geqslant 0, \quad \forall\ h = 1, 2, \ldots, S \tag{5.48}$$

$$Ex[\mathcal{Z}^h_2] - \sum_{h=1}^{S} \rho^h Ex[\mathcal{Z}^h_2] + \upsilon^h_2 \geqslant 0, \quad \forall\ h = 1, 2, \ldots, S \tag{5.49}$$

$$\text{Ch}\left\{\sum_{i\in I'}\sum_{v\in V_n} x_{ijv}^{pt} + B1_{kp}^{t} - B1_{kp}^{t-1} + Q3_{jp}^{t-1} \geqslant \zeta_{dm_{jp}^{t}}\right\} \geqslant \alpha_{jp}^{t}, \quad \forall\ j\in J, \forall\ p\in P', \forall\ t\in T \tag{5.50}$$

$$\text{Ch}\left\{\sum_{i\in I''}\sum_{v\in V_r} y_{ijv}^{pt} + B1_{kp}^{t} - B1_{kp}^{t-1} + Q3_{jp}^{t-1} \geqslant \zeta_{dm_{jp}^{t}}\right\} \geqslant \beta_{jp}^{t}, \quad \forall\ j\in J, \forall p\in P'', \forall\ t\in T \tag{5.51}$$

$$\text{Ch}\left\{\sum_{v\in V_j} A_{kvp}^{t} + B2_{kp}^{t} - B2_{kp}^{t-1} \geqslant \zeta_{dem_{kp}^{t}}\right\} \geqslant \gamma_{jkp}^{t}, \quad \forall\ j\in J, \forall\ k\in H_j, \forall\ p\in P, \forall\ t\in T \tag{5.52}$$

$$\sum_{i\in I''}\sum_{v\in V_r} z_{jiv}^{pt} = E\left[\zeta_{\theta_p}\right]\sum_{v\in V_j}\sum_{k\in H_j} F_{kjv}^{pt}, \quad \forall\ j\in J, \forall\ p\in P'', \forall\ t\in T \tag{5.53}$$

$$\sum_{m\in M}\sum_{v\in V_r} w_{jmv}^{pt} = \left(1 - E\left[\zeta_{\theta_p}\right]\right)\sum_{v\in V_j}\sum_{k\in H_j} F_{kjv}^{pt}, \quad \forall\ j\in J, \forall\ p\in P'', \forall\ t\in T \tag{5.54}$$

$$\sum_{v\in V_j} R_{kvp}^{t} = E\left[\zeta_{\lambda_k^p}\right]\sum_{v\in V_j} A_{kvp}^{t-1}, \quad \forall\ j\in J, \forall\ k\in H_j, \forall\ p\in P'', \forall\ t\in T \tag{5.55}$$

$$\text{Ch}\left\{B1_{jp}^{t} \leqslant \pi 1_p^t \zeta_{dm_{jp}^{t}}\right\} \geqslant \varepsilon_{jp}^{t}, \quad \forall\ j\in J, \forall\ p\in P, \forall\ t\in T \tag{5.56}$$

$$\text{Ch}\left\{B2_{kp}^{t} \leqslant \pi 2_p^t \zeta_{dem_{kp}^{t}}\right\} \geqslant \nu_{jkp}^{t}, \quad \forall\ j\in J, \forall\ k\in H_j, \forall\ p\in P, \forall\ t\in T \tag{5.57}$$

constraints (4.5)−(4.14), (4.18), (4.22)−(4.31), (4.34)−(4.47).
Here $\alpha_{jp}^t, \beta_{jp}^t, \gamma_{jkp}^t, \varepsilon_{jp}^t, \nu_{jkp}^t$ are the satisfaction levels for respective constraints, and a_1 and a_2 are the risk tolerances for the objective functions one and two respectively. Chance constraints are transformed into their following equivalent form using Definitions 2.7 and 2.8.
Also

$$Ex[\mathcal{Z}_1^h] = Ex[\text{TC}^h] = Ex[\text{PRC}^h] + Ex[\text{DIC}^h] + Ex[\text{IHC}^h],$$

$$\begin{aligned} Ex[\mathcal{Z}_2^h] = &\sum_{j\in J}\sum_{t\in T}\left[\sum_{i\in I'}\sum_{v\in V_n}\sum_{p\in P'} Ex\left[\tau_{t_v}^h\right]\left(x_{ijv}^{pt}/c_v\right)d_{ij} + \sum_{i\in I''}\sum_{v\in V_r}\sum_{p\in P''} Ex\left[\tau_{t_v}^h\right]\left(y_{ijv}^{pt}/c_v\right)d_{ij}\right] + \\ &\sum_{j\in J}\sum_{v\in V_r}\sum_{p\in P''}\sum_{t\in T}\left[\sum_{i\in I''} Ex\left[\tau_{t_v}^h\right]\left(z_{jiv}^{pt}/c_v\right)d_{ji} + \sum_{m\in M} Ex\left[\tau_{t_v}^h\right]\left(w_{jmv}^{pt}/c_v\right)d_{jm}\right] + \\ \sum_{j\in J}\sum_{k_1\in H_j}\sum_{k_2\in H_j}\sum_{v\in V_j}\sum_{t\in T}&\left[Ex\left[\tau_{et_v}^h\right]\delta_{k_1k_2v}^t + Ex\left[\tau_{at_v}^h\right]\left(\sum_{p\in P} L_{k_1k_2v}^{pt} + \sum_{p\in P''} F_{k_1k_2v}^{pt}\right)/c_v\right]d_{k_1k_2}, \end{aligned}$$

$$Ex[\text{PRC}^h] = \sum_{t\in T}\left[\sum_{i\in I'}\sum_{p\in P'} Ex\left[\tau_{pc_p^1}^h\right]X_{ip}^t + \sum_{i\in I''}\sum_{p\in P''}\left(Ex\left[\tau_{pc_p^2}^h\right]Y_{ip}^t + Ex\left[\tau_{rc_p}^h\right]Z_{ip}^t\right)\right],$$

$$Ex[\text{DIC}^h] = \sum_{i\in I''}\sum_{j\in J}\sum_{v\in V_r}\sum_{p\in P''}\sum_{t\in T}\left[Ex\left[\tau_{tc_v}^h\right]y_{ijv}^{pt}d_{ij} + Ex\left[\tau_{tc_v}^h\right]z_{jiv}^{pt}d_{ji}\right] +$$

$$\sum_{j\in J}\sum_{t\in T}\left[\sum_{i\in I'}\sum_{v\in V_n}\sum_{p\in P'} Ex\left[\tau^h_{tc_v}\right] x^{pt}_{ijv} d_{ij} + \sum_{m\in M}\sum_{v\in V_r}\sum_{p\in P''} Ex\left[\tau^h_{tc_v}\right] w^{pt}_{jmv} d_{jm}\right] +$$

$$\sum_{j\in J}\sum_{k_1\in H_j}\sum_{k_2\in H_j}\sum_{v\in V_j}\sum_{t\in T}\left[Ex\left[\tau^h_{etc_v}\right]\delta^t_{k_1k_2v} + Ex\left[\tau^h_{atc_v}\right]\left(\sum_{p\in P} L^{pt}_{k_1k_2v} + \sum_{p\in P''} F^{pt}_{k_1k_2v}\right)\right] d_{k_1k_2},$$

$$Ex[\mathrm{IHC}^h] = \sum_{t\in T}\left[\sum_{i\in I'}\sum_{p\in P'} Ex\left[\tau^h_{hc^1_{ip}}\right] Q1^t_{ip} + \sum_{i\in I''}\sum_{p\in P''} Ex\left[\tau^h_{hc^2_{ip}}\right] Q2^t_{ip} + \sum_{j\in J}\sum_{p\in P} Ex\left[\tau^h_{hc^3_{jp}}\right] Q3^t_{jp}\right],$$

and

- Z_κ Objective function for $\kappa = 1, 2, 3, 4$,
- $\mathcal{Z}^h_\kappa$ Uncertain objective function for $\kappa = 1, 2$ under scenario h,
- ρ^h Probability of occurring scenario h,
- $\tau^h_{t_v}$ Uncertain time required by fully loaded v^{th} vehicle for travelling per unit distance under scenario $h, v \in V_n \cup V_r$,
- $\tau^h_{et_v}, \tau^h_{at_v}$ Uncertain time required by empty and additionally loaded v^{th} vehicle for shipping per unit product per unit distance under scenario $h, v \in V_j$,
- $\tau^h_{tc_v}$ Uncertain transportation cost of v^{th} vehicle for shipping per unit product per unit distance under scenario $h, v \in V_n \cup V_r$,
- $\tau^h_{etc_v}, \tau^h_{atc_v}$ Uncertain transportation cost of empty and additionally loaded v^{th} vehicle for shipping per unit product per unit distance under scenario $h, v \in V_j$,
- $\tau^h_{pc^1_p}$ Uncertain production cost for per unit NRP p under scenario h,
- $\tau^h_{pc^2_p}, \tau^h_{rc_p}$ Uncertain production and recovery cost respectively for per unit RP p in scenario h,
- $\tau^h_{hc^1_{ip}}$ Uncertain holding cost for per unit NRP p in i^{th} NRPC under scenario h,
- $\tau^h_{hc^2_{ip}}$ Uncertain holding cost for per unit RP p in i^{th} RPRC under scenario h,
- $\tau^h_{hc^3_{jp}}$ Uncertain holding cost for per unit product p in j^{th} TCC under scenario h.

5.1 Solving procedure of RO model

Model 1 is an MOMIP problem with four conflicting objective functions that can be solved by multi-objective optimization technique. However, we apply augmented weighted Tchebycheff method to solve Model 1. The main advantage of this method is, it eliminates weakly non-dominated solutions. This method operates by considering each objective function individually, and then by solving augmented weighted Tchebycheff program, given below, it provides a “balanced” solution.

Model 2

$$
\begin{aligned}
\text{minimize} \quad & \mathcal{W} \\
\text{subject to} \quad & \mathcal{W} \geqslant \varpi_\kappa(t)\left(\mathcal{Z}_\kappa - \mathcal{Z}_\kappa^*\right) + \epsilon \sum_{\kappa=1}^{4} \left(\mathcal{Z}_\kappa - \mathcal{Z}_\kappa^*\right), \quad \forall\, \kappa = 1,2,3,4, \\
& \text{constraints } (4.5) - (4.14), \\
& \text{constraints } (4.18), \\
& \text{constraints } (4.22) - (4.31), \\
& \text{constraints } (4.34) - (5.57).
\end{aligned}
$$

Here $\mathcal{Z}_\kappa^*$ is the ideal or utopia point of the objective function $\mathcal{Z}_\kappa, \kappa = 1,2,3,4$; ϵ is a very small number, and $\varpi_\kappa(t)$ is considered as weight assigning to three objective functions which varies from period to period satisfying the condition $\sum_{\kappa=1}^{4} \varpi_\kappa(t) = 1, \forall\, t$. Regarding the above fact the weights for the objective functions are considered as:

$$
\begin{cases}
\varpi_1(t) = -0.02t + 0.32 \\
\varpi_2(t) = 0.01t + 0.14 \\
\varpi_3(t) = 0.02t + 0.28 \\
\varpi_4(t) = -0.01t + 0.26
\end{cases}
$$

Variation of weights with time period is depicted in Fig. 4.

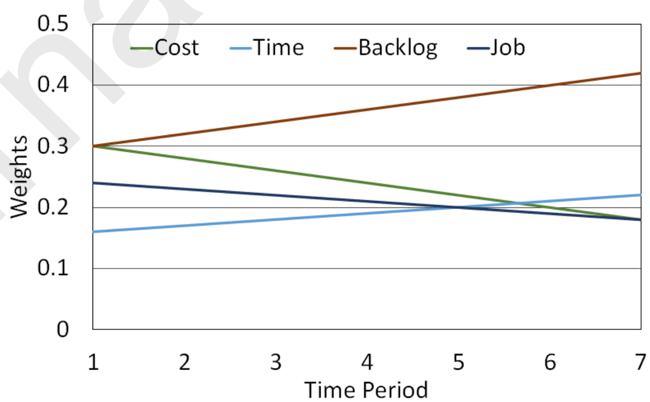


Fig. 4: Variation of weights with time periods.

6 Computational experiment

In order to asses the performance of the proposed uncertain-random SOCLSC model and proposed solving procedure, numerical problems are implemented and then the corresponding results are discussed in this section.

Table 3: Description of test problems.

Description	Test problem 1	Test problem 2	Test problem 3
NRPC	1	2	4
RPRC	2	3	3
TCC	2	3	5
DC	1	1	2
Vehicles available in NRPCs	2	3	7
Vehicles available in RPRCs	3	4	6
NRP	1	2	4
RP	2	3	3
Periods	2	3	4
Hospitals	10; $\lvert H_j \rvert = 5,\ j = 1, 2.$	15; $\lvert H_j \rvert = 5,\ j = 1, 2, 3.$	30; $\lvert H_j \rvert = 6,\ j = 1, 2, \ldots, 5.$
Vehicles available in TCCs	6; $\lvert V_j \rvert = 3,\ j = 1, 2.$	12; $\lvert V_j \rvert = 4,\ j = 1, 2, 3.$	20; $\lvert V_j \rvert = 4,\ j = 1, 2, \ldots, 5.$

6.1 Test problems

Here three test problems with different sizes are chosen. The values of all uncertain-random as well as deterministic parameters are generated randomly from the data, listed in Table 4. As given in Table 4, the uncertain-random parameters are considered as simple uncertain-random variables composed with linear uncertain variables under three scenarios with probabilities 0.25, 0.35, 0.4 respectively. Test problems are implemented according to the format that described in Table 3. As NRPs, various types of medicines, food products etc. are produced and supplied by several NRPCs, and as RPs, various types of masks, medical equipments etc. are produced, recovered and supplied by several RPRCs to several hospitals situated in COVID-19 areas through several TCCs.

6.2 Utilization of demand priority

The demand priorities of TCCs in different test problems are calculated by MADM method that is described in subsection 4.1 by considering the values of α, β as 0.4, 0.2 respectively and $w_l = 0.4, 0.3, 0.2, 0.1$ for four attributes respectively. Data related to four attributes are randomly generated from Table 4. Priorities are utilized to estimate the value of the parameters related to TCCs such as backlog fraction and demand. As an example, in test problem 1 the priorities of two TCCs in period 1 are calculated as 0.512 and 0.488, so the backlog fraction is set as, backlog fraction for TCC1 < backlog fraction for TCC2 and the demands of TCCs are set as: $\tau^h_{dm^t_{jp}} = \left(\frac{1}{1-\mathrm{pr}^t_j}\right) \sum_{k \in H_j} \tau^h_{dem^t_{kp}}, \ \forall j, p, t, h$. Also, safety stocks at TCCs are calculated according to their priorities (constraints (4.12)−(4.13)).

Table 4: Data source for generating parameters of the test problems.

Parameter		Range		
		Certain parameters	Uncertain parameters $\mathcal{L}(a_l, a_u)$	
jv_f^t		$\mathcal{U}(3-10)$		
$js_{nn'}^t$		$\mathcal{U}(2-5)$		
cf_j^p		$\mathcal{U}(2500-3500)$		
ci_j^p		$\mathcal{U}(1000-1500)$		
cr_i^p		$\mathcal{U}(800-1200)$		
dr_m^p		$\mathcal{U}(500-1000)$		
rr_j^p		$\mathcal{U}(1000-1500)$		
$s1_{ip}, s2_{ip}$		$\mathcal{U}(1000-1500)$		
$\pi1_{pt}, \pi2_{pt}$		$\mathcal{U}(.45-.6)$		
c_v		$\mathcal{U}(1500-4000)$		
m_{ip}^1, m_{ip}^2		$\mathcal{U}(.25-.4)$		
$m1_{i\ max}^t, m2_{i\ max}^t$		$\mathcal{U}(1500-3000)$		
ζ_{tc_v}	Scenario 1		$\mathcal{U}(.110, .112)$	$\mathcal{U}(.112, .114)$
	Scenario 2		$\mathcal{U}(.108, .110)$	$\mathcal{U}(.110, .112)$
	Scenario 3		$\mathcal{U}(.112, .114)$	$\mathcal{U}(.114, .116)$
ζ_{etc_v}	Scenario 1		$\mathcal{U}(.033, .035)$	$\mathcal{U}(.035, .037)$
	Scenario 2		$\mathcal{U}(.032, .034)$	$\mathcal{U}(.034, .036)$
	Scenario 3		$\mathcal{U}(.038, .04)$	$\mathcal{U}(.042, .044)$
ζ_{atc_v}	Scenario 1		$\mathcal{U}(.000013, .000015)$	$\mathcal{U}(.000015, .000017)$
	Scenario 2		$\mathcal{U}(.000016, .000018)$	$\mathcal{U}(.000018, .00002)$
	Scenario 3		$\mathcal{U}(.000015, .000017)$	$\mathcal{U}(.000017, .000019)$
ζ_{t_v}	Scenario 1		$\mathcal{U}(.068, .082)$	$\mathcal{U}(.072, .086)$
	Scenario 2		$\mathcal{U}(.063, .088)$	$\mathcal{U}(.067, .092)$
	Scenario 3		$\mathcal{U}(.063, .082)$	$\mathcal{U}(.067, .086)$
ζ_{et_v}	Scenario 1		$\mathcal{U}(.016, .018)$	$\mathcal{U}(.018, .02)$
	Scenario 2		$\mathcal{U}(.015, .019)$	$\mathcal{U}(.019, .021)$
	Scenario 3		$\mathcal{U}(.022, .024)$	$\mathcal{U}(.024, .026)$
ζ_{at_v}	Scenario 1		$\mathcal{U}(.000016, .000018)$	$\mathcal{U}(.000018, .00002)$
	Scenario 2		$\mathcal{U}(.000015, .000019)$	$\mathcal{U}(.000019, .000021)$
	Scenario 3		$\mathcal{U}(.000022, .000024)$	$\mathcal{U}(.000024, .000026)$
$\zeta_{pc_p^1}, \zeta_{pc_p^2}$	Scenario 1		$\mathcal{U}(41, 49)$	$\mathcal{U}(49, 57)$
	Scenario 2		$\mathcal{U}(43, 51)$	$\mathcal{U}(50, 58)$
	Scenario 3		$\mathcal{U}(45, 52)$	$\mathcal{U}(52, 59)$
ζ_{rc_p}	Scenario 1		$\mathcal{U}(11, 16)$	$\mathcal{U}(18, 23)$
	Scenario 2		$\mathcal{U}(13, 18)$	$\mathcal{U}(20, 25)$
	Scenario 3		$\mathcal{U}(15, 20)$	$\mathcal{U}(22, 27)$
$\zeta_{hc_{ip}^1}, \zeta_{hc_{ip}^2}$	Scenario 1		$\mathcal{U}(7, 24)$	$\mathcal{U}(17, 30)$
	Scenario 2		$\mathcal{U}(8, 25)$	$\mathcal{U}(18, 35)$
	Scenario 3		$\mathcal{U}(9, 26)$	$\mathcal{U}(20, 40)$
$\zeta_{hc_{jp}^3}$	Scenario 1		$\mathcal{U}(6, 14)$	$\mathcal{U}(16, 24)$
	Scenario 2		$\mathcal{U}(7, 15)$	$\mathcal{U}(18, 26)$
	Scenario 3		$\mathcal{U}(8, 16)$	$\mathcal{U}(20, 28)$
$\zeta_{dem_{kp}^t}$	Scenario 1		$\mathcal{U}(100, 150)$	$\mathcal{U}(200, 250)$
	Scenario 2		$\mathcal{U}(110, 160)$	$\mathcal{U}(210, 260)$
	Scenario 3		$\mathcal{U}(115, 165)$	$\mathcal{U}(215, 265)$
$\zeta_{\theta_p}, \zeta_{\lambda_{kp}^t}$	Scenario 1		$\mathcal{U}(.4, .55)$	$\mathcal{U}(.45, .65)$
	Scenario 2		$\mathcal{U}(.45, .6)$	$\mathcal{U}(.55, .7)$
	Scenario 3		$\mathcal{U}(.5, .7)$	$\mathcal{U}(.55, .8)$
Affected people		$\mathcal{U}(150-300)$		
Population density		$\mathcal{U}(900-1200)$		
Aged population		$\mathcal{U}(90-210)$		
Survived and dead people percentage		$\mathcal{U}(65-80)$		

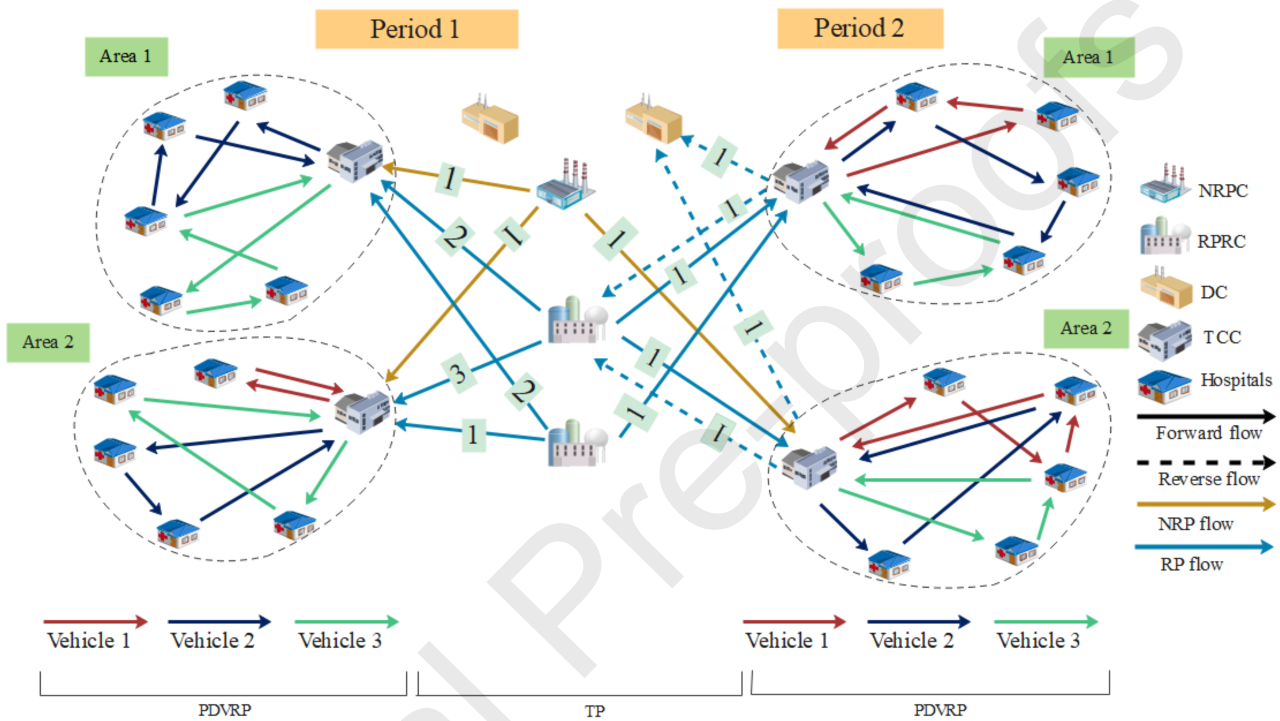


Fig. 5: Optimal routes of vehicles for test problem 1.

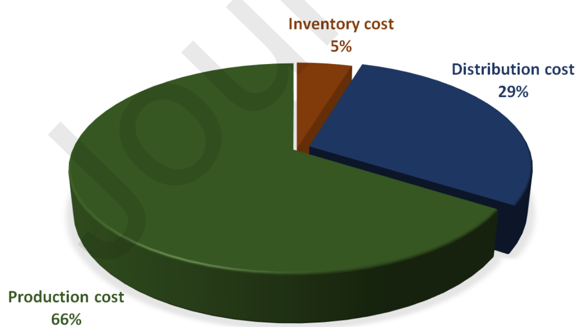


Fig. 6: Components of total cost.

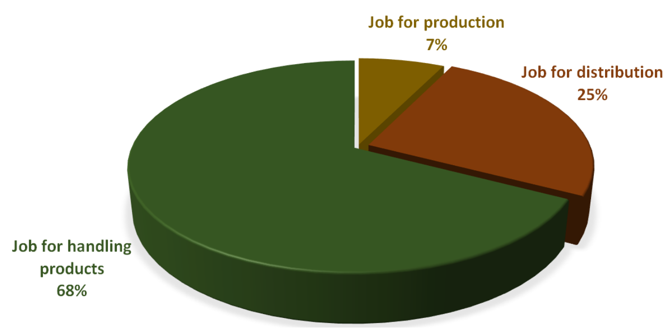


Fig. 7: Components of total job.

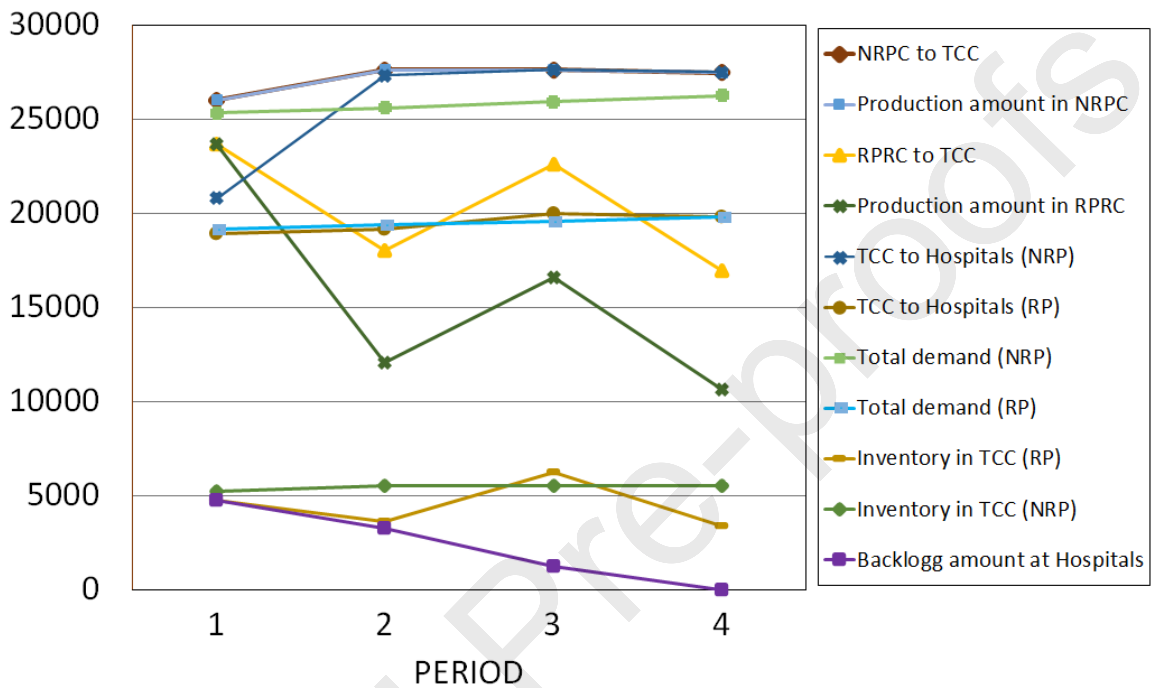


Fig. 8: Optimal flows in forward network.

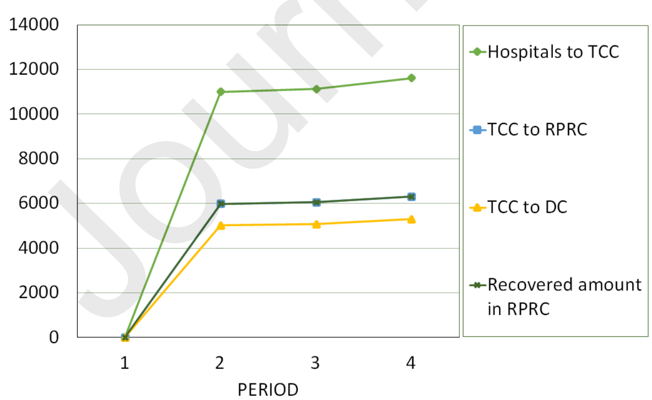


Fig. 9: Optimal flows in reverse network.

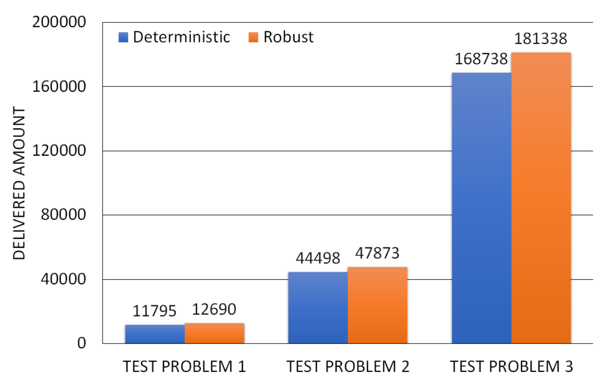


Fig. 10: Delivered amount to the hospitals.

Table 5: Values of the objective functions in different test problems.

Scenario	Deterministic				Robust			
	Cost	Time	Backlog amount	Job	Cost	Time	Backlog amount	Job
Test problem 1								
–	941189	88.69	1421.43	118.47				
1					1025110	95.22	1139.86	127.6
2					1045280	92.78	1139.86	127.6
3					1068500	98.36	1139.86	127.6
Mean value	941189	88.69	1421.43	118.47	1049520	95.62	1139.86	127.6
Test problem 2								
–	3513620	286.96	4272.77	623.63				
1					3782000	312.72	6294.2	684.66
2					3847160	302.6	6294.2	684.66
3					3931000	317.78	6294.2	684.66
Mean value	3513620	286.96	4272.77	623.63	3864406	311.2	6294.2	684.66
Test problem 3								
–	12458800	722.44	7161.01	2128.5				
1					13187400	780.46	12800.8	2314.35
2					13382800	785.19	12800.8	2314.35
3					13660200	782.80	12800.8	2314.35
Mean value	12458800	722.44	7161.01	2128.35	13444900	782.8	12800.8	2314.35

6.3 Results and discussion

Using the expected values of the uncertain-random parameters, defined in Remark 2.1 the uncertain model is transformed into its equivalent deterministic form, namely expected value model (EVM), which is also solved by AWTM, which is described in subsection 5.1, and without direct transforming into deterministic form, first the uncertain-random robust counterpart model of the proposed model is developed and then the robust counterpart model is solved by AWTM. The satisfaction levels of the constraints are all considered as 0.8. The results are depicted in Table 5. All the computations are carried out in AMPL optimization software by Gurobi 9.0.2 on 2.10 GH CPU with 8 GB RAM.

To provide a basic notion of the network, Fig. 5 is inserted, which also exposes the optimal routes of the vehicles for first and second stages in two periods, obtained by solving test problem 1. As shown in Fig. 5, more vehicles are active for first stage in period 1 than in period 2, this happens because delivery amounts from production centers to TCCs are reduced in second period as previous period's inventory stocks are present in TCCs for further distribution, furthermore, in NRPC one vehicle is not used in both periods as other one is capable to transport products to all TCCs. Although, in second stage, it happens in opposite scenario, i.e., vehicles are more active in period 2 than period 1, as vehicles only have to make delivery in period 1 but have to make delivery as well as pick-up in period 2. Also, it can be observed that in second stage, hospitals are accessed more than once and receive split demands.

The components of the economical and social objective function, i.e., total cost and total created job in solutions of test problem 3 are shown in Figs. 6 and 7 respectively. According to Fig. 6, production and then distribution cost occupy most of the spaces in total cost, which indicates the model's liability to satisfy the demands. In the social objective function, most of the jobs are created for handling products at different facilities and distributing products, which can be justified as the network contains hybrid production-distribution or hybrid transfer-collection centers, so large amounts of products are gathered from forward and reverse flows in hybrid facilities which have to be handled and then shipped.

The optimal flows in forward and reverse network among facilities for two types of products are shown in Figs. 8 and 9 respectively, which are obtained by solving test problem 3. In Fig. 8, it can be seen that the demands of hospitals for two types of products are set to be increased as period increases. The delivered amount of NRPs to the hospitals in the first period is less than the demand due to backlog amount and always higher than the demand in other periods in order to meet the demand as well as previous period's backlog quantities, and for RPs it is almost same as the demands in all periods. Therefore, the resulting backlog amounts for two types of products in the hospitals are decreased in all periods and finally equal to zero at fourth period as shown in Fig. 8. It is also seen that, the production amounts in NRPCs go higher from first period to second then reduce in the rest periods, as delivery amounts to TCCs are decreased due to previous periods' inventory stock at TCCs, but in RPRCs production of new products are happened according to the returned and recovered amounts, which can be seen in Fig. 9. It is also evident from Fig. 8 that the inventory level in NRPC is always zero (as two lines at the top representing producing amount and delivered amount at NRPC are coincide), and the resulting inventories (new + recovered RPs) at RPRCs are also zero, all inventories are only at TCCs. In Fig. 9, it is seemed that there is no activity in reverse network for the first period, and in all other periods the reverse flows between facilities are almost identical except only in fourth period it is slightly higher than other periods, also in RPRC, all recoverable RPs are recovered in all periods as two lines representing received recoverable amounts RPs from TCCs and recovered amounts of RPs at RPRCs are coincide.

6.4 Validation

This section shows the validations of the proposed model and approach. All experiments are conducted by solving test problem 1.

6.4.1 Validation of the proposed model

In this section, we first investigate the impact of the minimum satisfaction levels (SLs) of the constraints on the total cost and depict the report in Fig. 11. From Fig. 11, we see that as SL increases, total cost also increases. This happens because when SL increases, demanded quantities of the hospitals also increase. So the whole system tends to satisfy the increased demand and the hospitals receive more amount (can be verified from Fig. 11). Thus the resultant total cost increases.

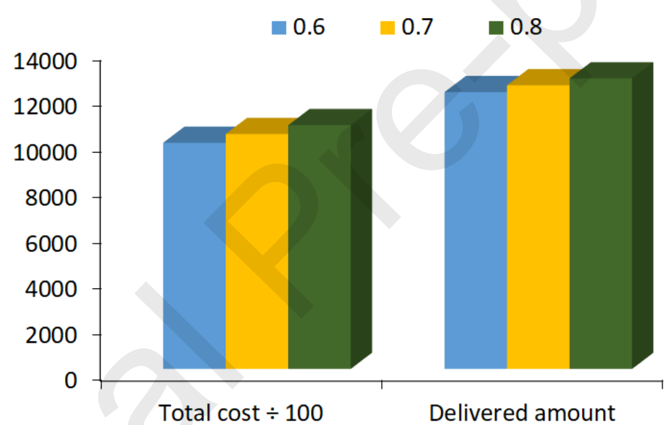


Fig. 11: Total cost and delivered amount vs. satisfaction level.

Again we analyse the trade-off between two uncertain objective functions i.e., total cost and total time, under different risk tolerance levels. To do this, we solve the robust model with the above-mentioned objective functions by LP-metric method assigning same weights with risk tolerances (a_1 and a_2) 0, 10, 20, 30 and 40, and the results are reported in Table 6 and are portrayed in Fig. 12. From Table 6 and Fig. 12, it is easily seen that when a_1 is constant, total cost increases as a_2 increases. But when a_2 is constant, total time increases only when a_1 changes from 0 to 10 and almost similar in the higher values of a_1 (10 to 40). It is happened because the risk tolerances associated with two objective functions represent their respective importance. So increasing the risk tolerance of one objective function opposes to the importance of the other and increases the value of the other objective function.
Also, to validate the proposed model, we randomly generate 10 realizations of the uncertain-random parameters under 5 risk tolerances (0, 50, 100, 150 and 200). The uncertain parameter ($\mathcal{L}(a_l, a_u)$) in each scenario is randomly generated by assigning the values from the

Table 6: Values of two uncertain objective functions under different risk tolerances and satisfaction levels.

Risk tolerance		Cost			Time		
		Satisfaction level			Satisfaction level		
a_1	a_2	0.6	0.7	0.8	0.6	0.7	0.8
0	0	980982	1015880	1050190	88.950	92.103	95.614
	10	981116	1016040	1050330	91.098	94.624	98.481
	20	975106	1012320	1050740	92.901	95.698	98.697
	30	1012370	1033810	1051010	95.208	96.796	98.697
	40	1013410	1036080	1053530	95.317	97.395	99.123
10	0	980982	1016180	1050740	89.026	92.180	95.793
	10	981423	1017050	1050670	91.176	94.692	98.422
	20	975343	1012520	1050620	92.930	95.717	98.612
	30	1011660	1035420	1052020	94.869	97.162	98.956
	40	1014220	1035470	1053430	95.245	97.194	99.097
20	0	981236	1016180	1050760	89.004	92.153	95.733
	10	980117	1016390	1051490	91.554	94.701	98.697
	20	975314	10113470	1052560	92.853	95.695	99.010
	30	1013380	1036480	1052170	95.006	97.301	98.896
	40	1014410	1036920	1052870	95.308	97.393	98.796
30	0	981641	1016180	1050760	89.062	92.216	95.732
	10	977593	1013760	1050840	92.356	95.547	98.558
	20	976724	1014560	1051940	93.028	95.908	98.694
	30	1013230	1036410	1052080	94.985	97.261	98.908
	40	1014460	1036370	1053450	95.323	97.220	98.943
40	0	981641	1017160	1050760	89.087	92.334	95.734
	10	977819	1013680	1050670	92.229	95.693	98.463
	20	976552	1013980	1051060	92.977	95.762	98.586
	30	1012880	1036350	1052040	94.827	97.233	98.900
	40	1013730	1036260	1053190	95.081	97.196	98.885

interval (a_l, a_u) in each realization. The average and standard deviation of total cost which are computed from solving the robust model under 10 realizations at satisfaction levels 0.6, 0.7 and 0.8, are reported in Table 7. Also the behaviours of the average and standard deviation of cost against risk tolerances under different satisfaction levels are demonstrated in Fig. 13. Fig. 13 shows that the average and standard deviation increase as SL increases, but remain almost same as risk tolerance increases and become constant at the higher values of risk tolerances. This shows the stability of the model.

6.4.2 Validation of the proposed robust approach

Here, we examine the effect of the hybrid approach (robust + AWTM) on the performance of SC. At the best of our knowledge, there is no other existing approach that can be used to solve the SC model with uncertain-random parameters. So we compare the result of the hybrid approach with the deterministic approach (described in subsection 6.3). The optimal values of the four objective functions, obtained by solving deterministic EVM and robust

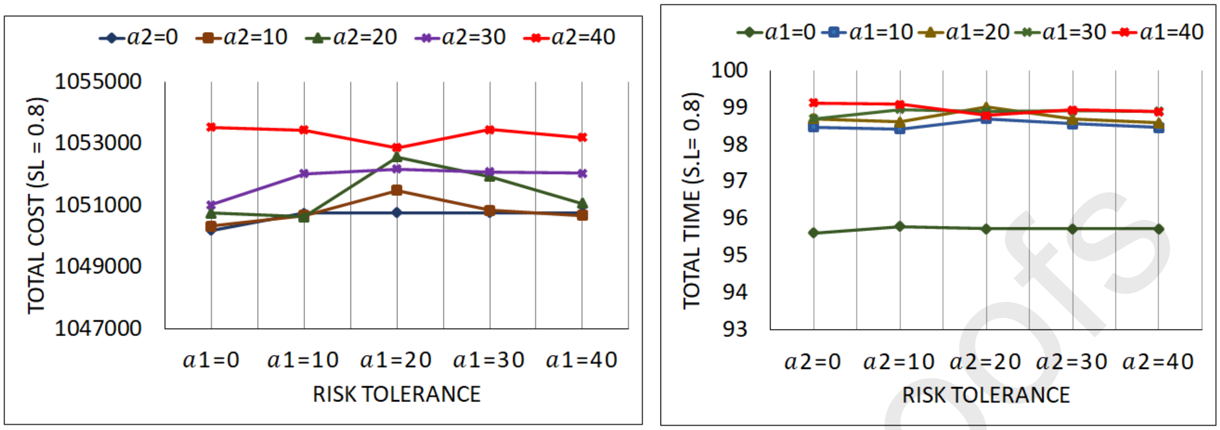


Fig. 12: Behaviours of two uncertain objective functions in different risk tolerances.

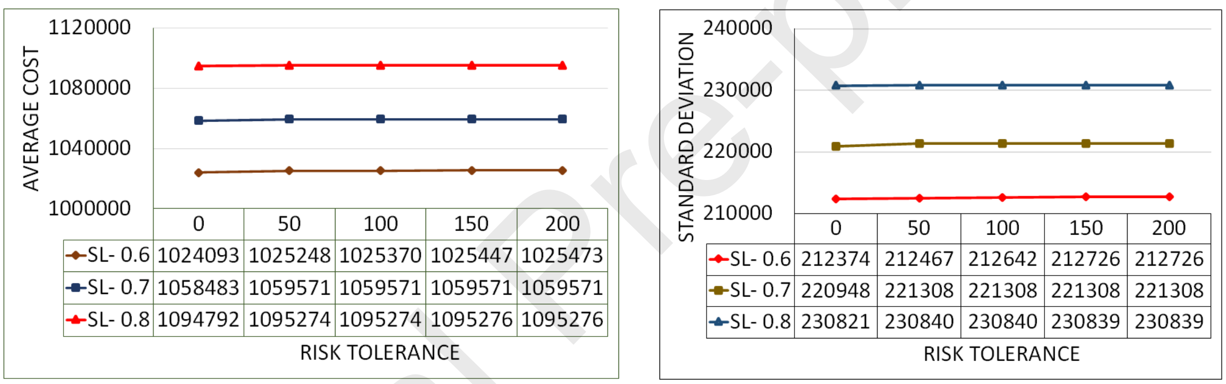


Fig. 13: Average cost and standard deviation vs. risk tolerances for realizations.

model for three test problems, considering same set of data, reported in Table 5. In three test problems robust model provides higher objective function values than deterministic models, reason of this is explained in Fig. 10. As per Fig. 10 in robust model, hospitals receive more amounts of products than deterministic model, this leads to more objective functions values due to more activity of the whole SC system. Thus, in hybrid approach the satisfaction degree of the hospitals will be higher.

6.5 Sensitivity analysis

This section is employed to explore the impact of demand and return rate on four objective functions. The sensitivity analyses are made by solving test problem 3.

Table 7: The performance of the proposed model under various risk tolerances and realizations.

Risk tolerance	0			50			100			150			200		
	Satisfaction level			Satisfaction level			Satisfaction level			Satisfaction level			Satisfaction level		
No. of Realization	0.6	0.7	0.8	0.6	0.7	0.8	0.6	0.7	0.8	0.6	0.7	0.8	0.6	0.7	0.8
1	920892	953838	990119	924038	955404	991233	924038	955404	991233	924038	955404	991253	924304	955404	991253
2	1083590	1096600	1115600	1083590	1096610	1115780	1083590	1096610	1115780	1083590	1096610	1115780	1083590	1096610	1115780
3	973629	1011060	1049410	975250	1012580	1049850	975250	1012580	1049850	975250	1012580	1049850	975250	1012580	1049850
4	1170250	1214510	1260630	1171550	1216220	1261050	1172090	1216220	1261050	1172090	1216220	1261050	1172090	1216220	1261050
5	661615	681070	700529	661616	681072	700529	661616	681072	700529	661616	681072	700529	661616	681072	700529
6	827186	859289	892253	828583	860453	892485	828583	860453	892485	828583	860453	892485	828583	860453	892485
7	1232920	1279470	1328080	1234280	1281230	1328500	1234280	1281230	1328500	1235050	1281230	1328500	1235050	1281230	1328500
8	917573	948033	978493	918286	948775	974264	918286	948775	974264	918286	948775	974264	918286	948775	974264
9	1400790	1453950	1511230	1401940	1455430	1511510	1402620	1455430	1511510	1402620	1455430	1511510	1402620	1455430	1511510
10	1052480	1087010	1121580	1053350	1087940	1122540	1053350	1087940	1122540	1053350	1087940	1122540	1053350	1087940	1122540
Average	1024093	1058483	1094792	1025248	1059571	1095274	1025370	1059571	1095274	1025447	1059571	1095276	1025473	1059571	1095276
Standard deviation	212374	220948	230821	212467	221308	230840	212642	221308	230840	212726	221308	230839	212726	221308	230839

6.5.1 Sensitivity analysis on return rate

In order to analyze the impact of return rate on four objective functions, we solve the problem by varying the return rate from 0 to 1 and the acquired results are depicted in Fig. 14. Activities of vehicles and facilities increase according to increasing return rate, and as result cost, time and job also increases, Fig. 14 also verifies that. But when return rate is greater than 0.8, cost decreases, as then new products' production rate is lower than recovery rate, and recovery cost is lower than new product's production cost. Also, no new job is created when return rate increases from 0.6 to 0.8, this explains that although return rate increases from 0.6 to 0.8, there is no need to expand capacity of the facilities or to assign new vehicles, so no new employment. Fig. 14 shows that total backlog amounts decrease as return rate increases but when return rate is greater than 0.6 it increases, reason for this may be the shortage of available machine time.

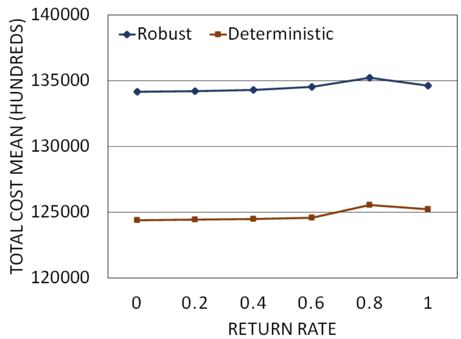
6.5.2 Sensitivity analysis on demand

We solve the problem for five different patterns of demand, -10%, -20%, main case, $+10\%$ and $+20\%$, to investigate the impact of demand in objective functions, and report is illustrated in Fig. 15. As per Fig. 15, total cost and total time increase linearly as demand increases, but backlog amounts increase with jump for increasing demand by 10% or more. Created total jobs increase if demand increases from main case, but decrease rate (from main case to -20%) is higher than increase rate (from main case to $+20\%$) according to Fig. 15.

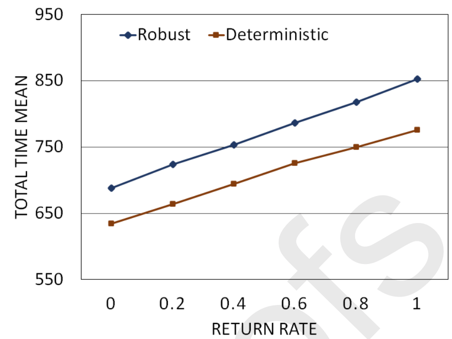
7 Managerial implications

The following managerial implications are derived from this research which can be valuable and significant in various governmental and private organizations associated with logistics and supply chain management.

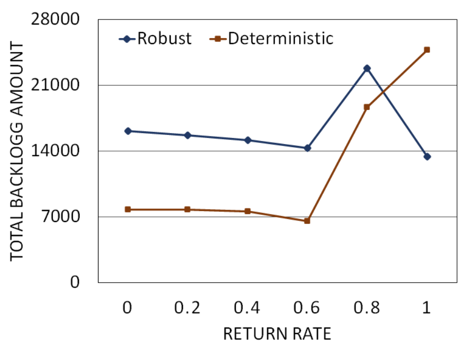
(i) The proposed SOCLSC model will help the managers to set up an integrated production-distribution process by conducting open- and closed-loop simultaneously in a single supply chain network. Managers can also conduct a parallel network with two different types of products (NRP and RP) in the proposed network without extra labours and expenses. In a critical situation like COVID-19 lock-down, the accounted aspects will help the organizations to preserve allocated budget (economical), to satisfy customers with on-time or prior delivery (satisfactory), to sustain the nice public image by giving jobs (social). By minimizing total backlog amount, hospitals can prevent the



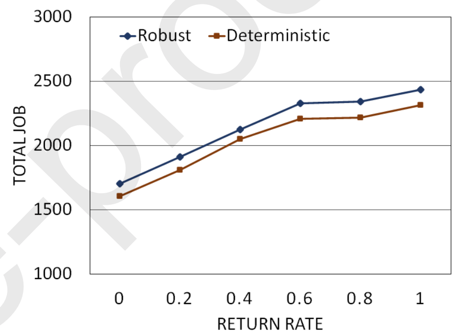
(a) Total cost vs. return rate.



(b) Total time vs. return rate.

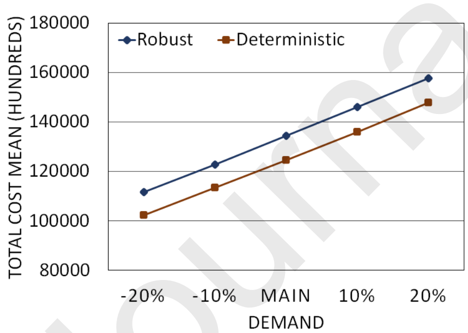


(c) Total backlog amount vs. return rate.

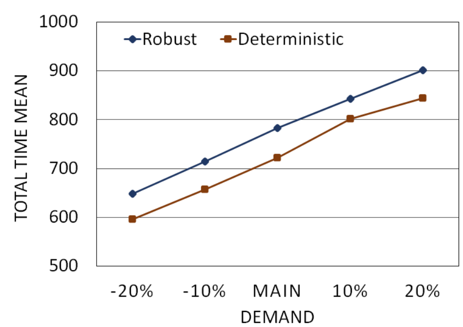


(d) Total job vs. return rate.

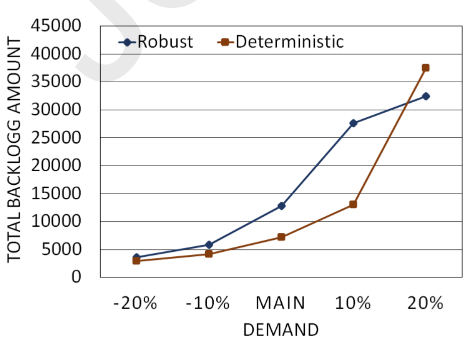
Fig. 14: Impact of return rate on four objective functions.



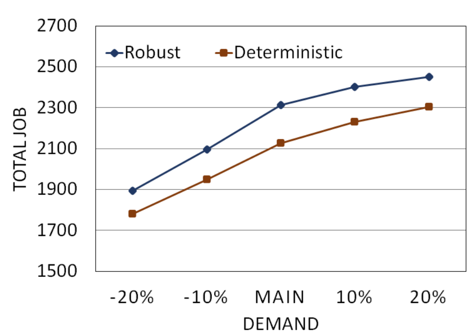
(a) Total cost vs. demand.



(b) Total time vs. demnad.



(c) Total backlog amount vs. demand.



(d) Total job vs. demand.

Fig. 15: Impact of demand on four objective functions.

shortage of the products in an emergency situation by receiving as much amount as possible.

(ii) The model will also be beneficial to illustrate the uncertain parameters in complicated circumstances. Since uncertainty is inevitable, and only single type uncertainty cannot limn the real-life parameters suitably in an emergency situation. Therefore the encountered mixed-uncertainty will help to figure out the parameters with the help of belief degrees as well as historical data by interacting among different scenarios.

(iii) In an urgent situation, priorities of the demand points play a vital role in distribution process. Otherwise extra damages or losses can be occurred in the affected areas. Thus the proposed MADM method can be used to derive the demand priorities of the affected areas in terms of urgency degrees to avoid extra damages. The proposed IFAHP considers the attributes as TrIFN, which is very realistic and logical, and gives entropy weights with less computational complexity.

(iv) As COVID-19 is a contagious disease, typical distribution network designs will not be very helpful to build a less contagious and flexible network system. To overcome the difficulties, decision makers can use the proposed composite network structure, which is a mixture of TP and PDVRP. By using this type of network structure, contagiousness which is occurred during the distribution process can be avoided safely.

(v) The output of the model can benefit the managers. The results which are obtained from three test problems can be helpful to the managers to use the more appropriate solution strategy. As example, robust model with higher satisfaction levels can be useful to the managers to provide higher amount of products to the hospitals (demand points) in emergency situations. Furthermore, validation and sensitivity analysis will help the managers to set the model parameters, satisfaction levels and risk tolerances. Also, by going through subsections 6.3-6.5, organizations can expand or reduce the components of different aspects which are smaller or larger than expectation, respectively, by sending preferable amounts of products to proper demand points.

8 Concluding remarks with future scopes

An integrated sustainable production-distribution-recovery system with opened- as well as closed-loop has been planned in this paper by optimizing economical, satisfactory and social aspects during COVID-19 emergency situation, considering multiple periods, multiple products and two stages. Hybrid facilities have been used in the model, which has resulted more cost saving and also more pollution reducing, caused from sharing materials handling equipments and infrastructure. To cope with uncertainty in network design, belief degrees as well as historical data of the parameters have been considered by treating them as simple uncertain-random variables, which have capability of handling multiple scenarios. Also, the distribution network has been designed by considering TP and PDVRP simultaneously. An MADM process, IFAHP has been approached to determine the demand priorities of the affected areas in terms of entropy weights, which have been used to estimate the parameters related to affected areas. Furthermore, a scenario-based uncertain-random robust counterpart model with chance constraints has been developed, and then the AWTM has been applied to solve the model. Finally, three test problems with randomly generated parameters have been demonstrated, and results along with sensitivity analysis on return rate and demand have been reported. The sensitivity analysis has showed that the objective functions are more sensitive to demand than return rate. The computational experiments have showed that the robust model has better performance in social sustainability measure, and also the robust model has handled data uncertainty in four objective functions with a reasonable increase. The proposed model has tendency to fulfil the demands as much as possible considering unsatisfied quantities, so it can be useful to design practical logistics network during emergency situations with higher or mixed type uncertainties in parameters, apart from this the IFAHP would be an effective tool for decision making in practical situations with multiple vague attributes.

Various possible research directions can be forwarded from this study. Considering environmental aspects alongside economical and social aspects in future, can extend this study. Researchers can also expand this study by considering maximizing responsiveness or minimizing risks of the network as an objective or by considering transshipment instead of transportation problem in this study. Moreover, this paper has not addressed time complexity. However, computational time increases when the size of the problems increases. Therefore several heuristic or meta heuristic algorithms can be developed to solve the large size problems in future.

Conflict of interest: Authors declare that, there is no conflict of interest of the paper.

References

[1] Afshar, A., and Haghani, A. Modeling integrated supply chain logistics in real-time large-scale disaster relief operations. *Socio-Economic Planning Sciences 46*, 4 (2012), 327–338.

[2] Alegoz, M., Kaya, O., and Bayindir, Z. P. Closing the loop in supply chains: Economic and environmental effects. *Computers & Industrial Engineering 142* (2020), Article

106366.

[3] Das, S. K., and Roy, S. K. Effect of variable carbon emission in a multi-objective transportation-p-facility location problem under neutrosophic environment. *Computers & Industrial Engineering 132* (2019), 311–324.

[4] Das, S. K., Roy, S. K., and Weber, G.-W. Application of type-2 fuzzy logic to a multiobjective green solid transportation–location problem with dwell time under carbon tax, cap, and offset policy: Fuzzy versus nonfuzzy techniques. *IEEE Transactions on Fuzzy Systems 28*, 11 (2020), 2711–2725.

[5] Das, S. K., Roy, S. K., and Weber, G. W. Heuristic approaches for solid transportation-p-facility location problem. *Central European Journal of Operations Research 28*, 3 (2020), 939–961.

[6] Dehghan, E., Nikabadi, M. S., Amiri, M., and Jabbarzadeh, A. Hybrid robust, stochastic and possibilistic programming for closed-loop supply chain network design. *Computers & Industrial Engineering 123* (2018), 220–231.

[7] Entezaminia, A., Heydari, M., and Rahmani, D. A multi-objective model for multi-product multi-site aggregate production planning in a green supply chain: Considering collection and recycling centers. *Journal of Manufacturing Systems 40* (2016), 63–75.

[8] Eydi, A., and Alavi, H. Vehicle routing problem in reverse logistics with split demands of customers and fuel consumption optimization. *Arabian Journal for Science and Engineering 44*, 3 (2019), 2641–2651.

[9] Fathollahi-Fard, A. M., Hajiaghaei-Keshteli, M., and Mirjalili, S. Multi-objective stochastic closed-loop supply chain network design with social considerations. *Applied Soft Computing 71* (2018), 505–525.

[10] Gholizadeh, H., and Fazlollahtabar, H. Robust optimization and modified genetic algorithm for a closed loop green supply chain under uncertainty: Case study in melting industry. *Computers & Industrial Engineering 147* (2020), Article 106653.

[11] Gilani, H., and Sahebi, H. A multi-objective robust optimization model to design sustainable sugarcane-to-biofuel supply network: the case of study. *Biomass Conversion and Biorefinery* (2020), 1–22, doi.org//10.1007/s13399–020–00639–8.

[12] Haghani, A., and Oh, S.-C. Formulation and solution of a multi-commodity, multi-modal network flow model for disaster relief operations. *Transportation Research Part A: Policy and Practice 30*, 3 (1996), 231–250.

[13] Liao, Y., Kaviyani-Charati, M., Hajiaghaei-Keshteli, M., and Diabat, A. Designing a closed-loop supply chain network for citrus fruits crates considering environmental and economic issues. *Journal of Manufacturing Systems 55* (2020), 199–220.

[14] Liu, B. *Uncertainty Theory - A Branch of Mathematics for Modeling Human Uncertainty*, vol. 300. Springer, 2010,.

[15] Liu, M., and Zhao, L. A composite weighted multi-objective optimal approach for emergency logistics distribution. In *2007 IEEE International Conference on Industrial Engineering and Engineering Management* (2007), IEEE, pp. 968–972.

[16] Liu, Y. Uncertain random variables: a mixture of uncertainty and randomness. *Soft Computing 17*, 4 (2013), 625–634.

[17] Mahapatra, D. R., Roy, S. K., and Biswal, M. P. Multi-choice stochastic transportation problem involving extreme value distribution. *Applied Mathematical Modelling 37*, 4 (2013), 2230–2240.

[18] Maity, G., Roy, S. K., and Verdegay, J. L. Time variant multi-objective interval-valued transportation problem in sustainable development. *Sustainability 11*, 21 (2019), 6161.

[19] Maity, G., Roy, S. K., and Verdegay, J. L. Analyzing multimodal transportation problem and its application to artificial intelligence. *Neural Computing and Applications 32* (2020), 2243–2256.

[20] Midya, S., Roy, S. K., and Vincent, F. Y. Intuitionistic fuzzy multi-stage multi-objective fixed-charge solid transportation problem in a green supply chain. *International Journal of Machine Learning and Cybernetics 12* (2020), 699–717.

[21] Mirzapour Al-E-Hashem, S., Malekly, H., and Aryanezhad, M. B. A multi-objective robust optimization model for multi-product multi-site aggregate production planning in a supply chain under uncertainty. *International Journal of Production Economics 134*, 1 (2011), 28–42.

[22] Moghaddam, Kamran S. Supplier selection and order allocation in closed-loop supply chain systems using hybrid monte carlo simulation and goal programming. *International Journal of Production Research 53*, 20 (2015), 6320–6338.

[23] Mon, D.-L., Cheng, C.-H., and Lin, J.-C. Evaluating weapon system using fuzzy analytic hierarchy process based on entropy weight. *Fuzzy Sets and Systems 62*, 2 (1994), 127–134.

[24] Nayagam, V. L. G., Jeevaraj, S., and Dhanasekaran, P. An improved ranking method for comparing trapezoidal intuitionistic fuzzy numbers and its applications to multicriteria decision making. *Neural Computing and Applications 30*, 2 (2018), 671–682.

[25] Nayeri, S., Paydar, M. M., Asadi-Gangraj, E., and Emami, S. Multi-objective fuzzy robust optimization approach to sustainable closed-loop supply chain network design. *Computers & Industrial Engineering 148* (2020), Article 106716.

[26] Qin, Z. Uncertain random goal programming. *Fuzzy Optimization and Decision Making 17*, 4 (2018), 375–386.

[27] Rabbani, M., Hosseini-Mokhallesun, S. A. A., Ordibazar, A. H., and Farrokhi-Asl, H. A hybrid robust possibilistic approach for a sustainable supply chain location-allocation network design. *International Journal of Systems Science: Operations & Logistics 7*, 1 (2020), 60–75.

[28] Roy, S. K., and Maity, G. Minimizing cost and time through single objective function in multi-choice interval valued transportation problem. *Journal of Intelligent & Fuzzy Systems 32*, 3 (2017), 1697–1709.

[29] Roy, S. K., and Midya, S. Multi-objective fixed-charge solid transportation problem with product blending under intuitionistic fuzzy environment. *Applied Intelligence 49*, 10 (2019), 3524–3538.

[30] Roy, S. K., Midya, S., and Vincent, F. Y. Multi-Objective Fixed-Charge Transportation Problem with Random Rough Variables. *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems 26*, 6 (2018), 971–996.

[31] Roy, S. K., Midya, S., and Weber, G.-W. Multi-objective multi-item fixed-charge solid transportation problem under twofold uncertainty. *Neural Computing and Applications 31*, 12 (2019), 8593–8613.

[32] Sheu, J.-B. An emergency logistics distribution approach for quick response to urgent relief demand in disasters. *Transportation Research Part E: Logistics and Transportation Review 43*, 6 (2007), 687–709.

[33] Soleimani, H., Chaharlang, Y., and Ghaderi, H. Collection and distribution of returned-remanufactured products in a vehicle routing problem with pickup and delivery considering sustainable and green criteria. *Journal of Cleaner Production 172* (2018), 960–970.

[34] Tofighi, S., Torabi, S. A., and Mansouri, S. A. Humanitarian logistics network design under mixed uncertainty. *European Journal of Operational Research 250*, 1 (2016), 239–250.

[35] Tzeng, G.-H., Cheng, H.-J., and Huang, T. D. Multi-objective optimal planning for designing relief delivery systems. *Transportation Research Part E: Logistics and Transportation Review 43*, 6 (2007), 673–686.

[36] Wang, D., Qin, Z., and Kar, S. A novel single-period inventory problem with uncertain random demand and its application. *Applied Mathematics and Computation 269* (2015), 133–145.

[37] Zahiri, B., Zhuang, J., and Mohammadi, M. Toward an integrated sustainable-resilient supply chain: A pharmaceutical case study. *Transportation Research Part E: Logistics and Transportation Review 103* (2017), 109–142.

[38] Zhalechian, M., Tavakkoli-Moghaddam, R., Zahiri, B., and Mohammadi, M. Sustainable design of a closed-loop location-routing-inventory supply chain network under mixed uncertainty. *Transportation Research Part E: Logistics and Transportation Review 89* (2016), 182–214.

[39] Zhen, L., Huang, L., and Wang, W. Green and sustainable closed-loop supply chain network design under uncertainty. *Journal of Cleaner Production 227* (2019), 1195–1209.

Credit author Statement:

Both the authors are equally contributed to the manuscript in all sections.