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Research Article

Modeling and Solving a Multi-objective Location-Routing Problem Considering the Evacuation of Casualties and Homeless People and Fuzzy Paths in Relief Logistics

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Abstract. The relief logistics and humanitarian supply chain in academic literature refer to the process of planning, execution, and effective controlling of the flow of costs and information and storage of necessary goods and materials from the point of origin to consumption with the primary purpose of reducing and relieving the affected people suffer. This paper discusses a multi-objective model for multi-period location-distribution-routing problems considering the evacuation of casualties and homeless people and fuzzy paths in relief logistics. Firstly, an uncertain multi-objective model of the problem was developed based on uncertain parameters of demand, time, and transport capacity, and then, using the fuzzy programming method, uncertain parameters of the problem were controlled. As the problem is NP-hard and GAMS software has not able to solve the model in larger sizes, meta-heuristic algorithms of NSGA-II and MOPSO were used to solve the problem.

Keywords. Relief logistics, Fuzzy programming, Uncertainty, Meta-heuristic algorithm.

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1 Introduction

Natural disasters usually cause serious damage to urban infrastructure and cause severe injury and death in populated areas. In recent years, much attention has been paid to these issues. In the case of natural disasters, rapid distribution of resources is essential to minimize damage and losses. A logistics operation that is carried out to help human beings in crises is called humanitarian logistics. Humanitarian logistics encompasses all processes for estimating, supplying, transporting, storing, and distributing goods, equipment, and services for injured people and relief teams. Logistics in normal circumstances and humanitarian logistics have similarities and differences, such as the similarities of supply chains in the normal and critical condition that the supply chain operates in a critical condition, as in ordinary circumstances, in two ways, forward and backward. In humanitarian logistics, in the forward mode, the goal is: to send and distribute goods and relief items, to send aid forces and medical and medical personnel, and in the backward mode, the collection and burial of the dead, the collection and transfer of injured to local or regional medical centers and the transfer of survivors to the safe (evacuation) areas. What distinguishes humanitarian logistics from ordinary logistics is that under critical conditions, the relief supply chain must act at high speed and aim to preserve human lives. While under ordinary circumstances, the supply chain operates at the lowest cost according to the schedule (Rawls et al., 2010) [17].

2 Literature Review

Emergency logistic operations are generally divided into two phases which are before and after the disaster. Since the focus of this paper is on the post-crisis phase and in the area of short-term and operational planning, an overview of the studies and researches carried out in this field is presented.

The first optimization models in emergency logistics were introduced in the late 1970s after a few marine disasters in the late 1960s and 1970s. Since the 1980s, research on other major disasters (such as storms, floods, and earthquakes) which happen on a large scale has also been included. Oh and Haqqani (1996) in [15] analyzed the transportation of large quantities of commodities such as food, clothing, medical supplies, drugs, machinery, and human resources into an effective approach to minimizing casualties with several types of transportation vehicles for relief operations; And Oudzamar and Laynet (2011) in [16] presented a mathematical model for transporting goods in the response phase, in which the vehicle travel time minima were considered. Bozorgi Amiri et al. (2011) presented a multi-disciplined randomized variable programming model under uncertain conditions [4]. They considered the parameters of demand, supply, and the cost of purchasing and transportation in their proposed model to be uncertain, and used a scenario-based approach. Muralie et al. (2012) considered the problem of the situation - the facility to find out the locations of the city that needs drug-to-be distributed among the population [14]. They considered the identification of the stored facilities and the coverage function intervals to maximize the coverage.

Anne et al. (2013), presented an article entitled ”Locating Displacement Transportation Facility under Facility Failure Conditions”, to plan the evacuation of many people living at an accidental site [2]. The goal is to minimize the cost of building a facility, the cost of transfer and, the cost of using the facility. Abu Naser et al. (2014) also developed a model for optimizing humanitarian relief centers by considering three goals of minimizing the total time of relief in damaged areas, minimizing the number of employees engaged in these centers, and maximizing the coverage of relief items over the damaged area [1]. This study considered only the definite demands of the damaged areas and only responded with a precise solution (ϵ-constraint) method. Zokaei et al. (2016) considered a three-level supply chain model, including suppliers, relief centers, and damaged districts for uncertain rescue operations and humanitarian relief [21]. Their model seeks to maximize the satisfaction of the affected people while minimizing the costs of the supply chain. Rezaei Malik et al. (2016) designed a two-objective model for handling natural disasters [18]. Their main goal in this article was to achieve optimal planning for degradable commodities such as medical items and milk in central warehouses before the disaster. The objective functions considered for their model included simultaneously minimizing the total operating costs before and after the incident and minimizing the average response time to demand points. In their model, they considered the parameters such as transportation time, demand, reliability and, cost of fines in a non-deterministic way. BozorgiAmiri et al. (2016) considered two issues of the evacuation of the wounded as well as the distribution of relief items simultaneously and used the constant optimization model to answer the problem’s uncertainty [5].

In the following, we study the other researches since 2017:

Hu et al. (2017) designed a randomized optimization model for joint inventory decisions before an incident and the transportation of humanitarian relief items after an accident [10]. In their model, they considered the demand parameter as an uncertain parameter and controlled the parameter by probabilistic optimization. Bonomi et al. (2017) reviewed the issues related to locating emergency logistics facilities based on various types of modeling and types of problems before and after the disaster [3]. They examined the problem of locating facilities in four types of definite, dynamic, probabilistic, and stable conditions, and described their solution and locating methods. Torabi et al. (2018) designed a humanitarian supply chain model based on the scenario and under uncertainty [19]. Their goal was to reduce the costs of the entire supply chain network, including the costs of locating, transportation, relief items maintenance, and fines in the case of the supply shortage. In their model, they considered parameters such as fixed costs of construction, transportation costs, and demand to be uncertain and used a scenario-based method. Yahyaei and BozorgiAmiri (2018) started to design a relief chain network under uncertainty [20]. Their main goal in this paper was to control the failure of distribution centers to meet the demand for demand centers as a reduction in investment costs. They also used a robust optimization method to control non-deterministic parameters and showed that total investment costs increase with increasing uncertainty. Alchy and Novian (2018) focused on modeling a scenario-based humanitarian supply chain network [8]. In their model, they looked at the optimal number and location of facilities, facility capacity, inventory levels, and transport network conditions under the uncertainty of demand after the incident. To solve their probable model, they used a shunt-cutting algorithm based on Bandar's breakdown.

This paper discusses a multi-objective model for multi-period location-distribution-routing problems considering the evacuation of casualties and homeless people and fuzzy paths in relief logistics. Some parameters are considered uncertain, including demand, the capacity of vehicles & time. Finally, NSGA-II and MOPSO as the meta-heuristic algorithms have been used to solve the problem in larger sizes.

3 Problem Definition and Modeling

In this paper, a six-level relief logistics issue (inventory of goods, relief distribution centers, damaged areas, temporary shelter sites, temporary medical centers, and hospitals) is considered. Given 1, the problem is considered for post-crisis and pre-crisis situations. Thus, in the pre-crisis conditions, some potential areas for the warehouse of goods, relief distribution centers, temporary accommodation centers, and temporary medical centers are considered, and in post-crisis situations, these centers are quickly located, and the allocation of goods and vehicle routing are dealt with. In this article, the damaged areas have two different types of demand. The first type of request relates to relief supplies and the second type is related to the transfer of survivors to other centers. The survivors in this type of network are divided into three categories. First-class injured people whose condition is critical and immediately transferred to hospitals with relief vehicles such as ambulances or helicopters. Second-class injured patients who have unclear conditions are transported to temporary care centers for treatment. After that, they will be transferred to hospitals if they have a critical condition. Otherwise, they will be transferred to temporary shelter sites. Third-class victims are homeless persons who move to temporary accommodation centers. At this stage, proper routing of vehicles between centers and also the optimal allocation of vehicles is important. On the other hand, the transportation of the injured person is not the only consideration, but it is necessary to send relief items toward affected areas and providing critical items such as water, blankets, and other items for homeless people in temporary accommodation centers. Therefore, the required items for each part are sent by the cargo vehicles from the warehouse to the relief distribution centers, and after the breakdown, relief items are sent to the affected areas while critical items are sent to the temporary accommodation centers. At this stage, the optimal routing of cargo vehicles is another issue. In addition, cargo and relief vehicles, depending on the type of problem and its vital importance, should choose the optimal route of transportation in the shortest possible time to transfer injured persons or emergency aid items. Therefore, in the design of such a network, the transmission time, demand, and capacity of vehicles are considered uncertain.

Given the definition of the stated problem, this is a multi-objective problem that pursues the following opposite objectives:

1. Minimizing total network costs, such as fixed costs of construction, transportation, and inventory

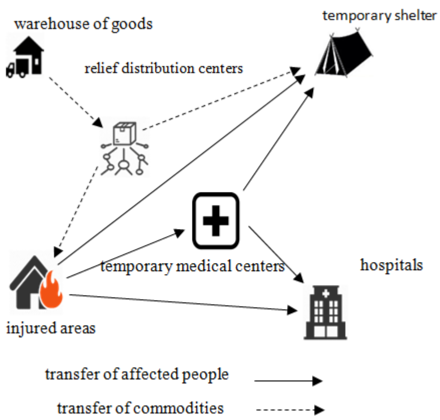

Figure 1: Proposed relief logistics network.

2. Minimize unsatisfied demand for relief items or transferring injured to other centers

3. Minimizing the total number of vehicles

In order to achieve the three above objectives simultaneously, it is important to determine the optimal location of the facility (inventory of goods, relief distribution centers, temporary accommodation centers, and temporary medical centers), optimal allocation of goods to other centers, and optimal routing of cargo and relief vehicles that all form the framework of the problem. With regard to the following assumptions, location-distribution-routing in the relief logistics will be modeled in uncertain conditions:

1. Transportation of survivors and distribution of relief items are considered together.

2. The fleet of vehicles is heterogeneous, and various types of vehicles are available.

3. Simultaneous transportation of goods and survivors in one vehicle is not possible.

4. Categorizing the survivors (1) the injured in a state of emergency; 2) an injured person whose condition is unclear and requires an initial examination; 3) the homeless people.

5. The amount of demand, the number of people in the three categories, the capacity of the vehicles, and the transmission time are uncertain.

6. The capacity of hospitals, temporary accommodation centers, temporary medical centers, relief distribution centers, and warehouses are specific parameters.

7. All centers within the network may receive goods or services from several related facilities.

Given the assumptions and objectives, the problem set, parameters and variables are presented in the next section.

3.1 Location-distribution-routing model in relief logistics

The set, parameters, and decision variables of the basic model are as follows:
Sets:

i :	set of affected areas by disaster $i = \{1, 2, \ldots, I\}$,
l :	set of potential shelter sites $l = \{1, 2, \ldots, L\}$,
m :	set of potential temporary medical centers $m = \{1, 2, \ldots, M\}$,
p :	set of potential relief distribution centers $p = \{1, 2, \ldots, P\}$,
h :	set of available hospitals $h = \{1, 2, \ldots, H\}$,
g :	set of potential warehouses of goods $g = \{1, 2, \ldots, G\}$,
t :	set of periods in the time horizon $t = \{1, 2, \ldots, T\}$,
k_1 :	set of vehicle types for carrying of relief commodities $k_1 = \{1, 2, \ldots, K_1\}$,
k_2 :	set of vehicle types for carrying of people $k_2 = \{1, 2, \ldots, K_2\}$,
k :	set of total vehicle types $k = k = K_1 \cup K_2$,
r :	set of survivors $r = \{R_A, R_b, R_c\}$,
e_1 :	set of relief commodities $e_1 = \{1, 2, \ldots, E_1\}$,
e_2 :	set of critical commodities $e_2 = \{1, 2, \ldots, E_2\}$,
e :	set of total commodity types $e = e_1 \cup e_2$.

Parameters:

$\widetilde{D1}_{i,r,t}$:	number of survivors type waiting at area i at time t,
$\widetilde{D2}_{i,e_1,t}$:	amount demanded of commodity type e_1 at area i at time t,
$\widetilde{D3}_{l,e_2,t}$:	amount demanded of commodity type e_2 at shelter l at time t,
$\widetilde{T\iota h}_{i,h,k_2}$:	The estimated time of travel of vehicle type k_2 from affected area i to hospital h,
$\widetilde{T\iota m}_{i,m,k_2}$:	The estimated time of travel of vehicle type k_2 from affected area i to temporary medical center m,
$\widetilde{T\iota mh}_{m,h,k_2}$:	The estimated time of travel of vehicle type k_2 from temporary medical center m to hospital h,
$\widetilde{T\iota gp}_{g,p,k_1}$:	The estimated time of travel of vehicle type k_1 from warehouse g to relief distribution center p,
$\widetilde{T\iota p\iota}_{p,i,k_1}$:	The estimated time of travel of vehicle type k_1 from relief distribution center p to affected area i,
$\widetilde{T\iota pl}_{p,l,k_1}$:	The estimated time of travel of vehicle type k_1 from relief distribution center p to temporary shelter sites l,
$\widetilde{Cap}_k$:	load capacity of vehicle type k,
$Trih_{i,h,k_2}$:	The estimated cost of travel of vehicle type k_2 from affected area i to hospital h,
$Trim_{i,m,k_2}$:	The estimated cost of travel of vehicle type k_2 from affected area i to temporary medical center m,
$Trmh_{m,h,k-2}$:	The estimated cost of travel of vehicle type k_2 from temporary medical center m to hospital h,

$Tril_{i,l,k_2}$: The estimated cost of travel of vehicle type $k-2$ from affected area i to temporary shelter sites l,
$Trml_{m,l,k_2}$: The estimated cost of travel of vehicle type k_2 from temporary medical center m to temporary shelter sites l,
$Trgp_{g,p,k_1}$: The estimated cost of travel of vehicle type k_1 from warehouse g to relief distribution center p,
$Tripi_{p,ik_1}$: The estimated cost of travel of vehicle type k_1 from relief distribution center p to affected area i,
$Trpl_{p,l,k_1}$: The estimated cost of travel of vehicle type k_1 from relief distribution center p to temporary shelter site l,
$CapL_{l,t}$: The capacity of temporary shelter site l for affected people type C at time t,
$CapM_{m,t}$: The capacity of temporary medical center m for affected people type B at time t,
$CapH_{h,t}$: The capacity of hospital h for affected people type A at time t,
$CapG_{g,e,t}$: The storage capacity of the commodity e at warehouse g at time t,
$CapP_{p,e,t}$: The storage capacity of the commodity e at the relief distribution center p at time t,
$Hd_{e_1,t}$: Inventory cost of commodity e_1 at time t,
$FixL_l$: Fixed cost for opening a new shelter center l,
$FixM_m$: Fixed cost for opening a new temporary medical center m,
$FixG_g$: Fixed cost for opening a new warehouse g,
$FixP_p$: Fixed cost for opening a new relief distribution center p,
$FixK_k$: Fixed cost for vehicle type k,
$NT_{k,t}$: Maximum number of vehicles type k available at time t,
F_{m,R_b} : percentage of affected people type B that transported to temporary shelter sites after cure at time t,
$BigM$: a big number,
$Mtime1$: Maximum time for transporting of injured people between network levels,
$Ntime2$: Maximum time for transporting of commodities between network levels,
ω : Normalization weight for second objective function.

Decision variables:

X_{i,h,r_a,t,k_2} : Number of survivors type A transported from affected area i to hospital h by,
Y_{i,m,r_b,t,k_2} : Number of survivorstype B transported from affected area i to temporary medical,
Z_{i,m,r_b,t,k_2} : Number of survivorstype C transported from affected area i to temporary shelter l,
U_{m,l,r_c,t,k_2} : Number of survivors type C transported from temporary medical center m to,
W_{m,h,r_a,t,k_2} : Number of survivorstype A transported from temporary medical center m to ,
O_{p,i,e_1,t,k_1} : Number of commodity type e_1 transported from relief distribution p to affected,
Q_{p,l,e_2,t,k_1} : Number of commodity type e_2 transported from relief distribution p to temporary,
N_{g,p,e,t,k_1} : Number of commodity type e transported from warehouse$g$ to relief distribution,
X'_{i,h,t,k_2} : $=1$, whether vehicle type k_2 travels across the route i to h at time, $t=0$, otherwise.
Y'_{i,m,t,k_2} : $=1$, whether vehicle type k_2 travels across the route i to m at time,

$t = 0$, otherwise.

Z'_{i,l,t,k_2} : $= 1$, whether vehicle type k_2 travels across the route i to l at time, $t = 0$, otherwise.

W'_{m,h,t,k_2} : $= 1$, whether vehicle type k_2 travels across the route m to h at time, $t = 0$, otherwise.

U'_{m,l,t,k_2} : $= 1$, whether vehicle type k_2 travels across the route m to l at time, $t = 0$, otherwise.

O'_{p,i,t,k_1} : $= 1$, whether vehicle type k_1 travels across the route p to i at time, $t = 0$, otherwise.

Q'_{p,l,t,k_1} : $= 1$, whether vehicle type k_1 travels across the route p to l at time, $t = 0$, otherwise.

N'_{g,p,t,k_1} : $= 1$, whether vehicle type k_1 travels across the route g to p at time, $t = 0$, otherwise.

ZM_m : $= 1$, whether a temporary medical center at m is open, $= 0$, otherwise.

ZL_l : $= 1$, whether a temporary shelter at l is open $= 0$, otherwise.

ZP_p : $= 1$, whether a relief distribution center at p is open, $= 0$, otherwise.

ZG_g : $= 1$, whether a warehouse at g is open, $= 0$, otherwise.

$No_{k,t}$: Number of used vehicles k at time t,

$In_{e_1,t}$: Amount of stored inventory of commodity type e_1 at time t,

$S1_{i,r,t}$: Number of unserved people type r in affected i area at time t,

$S2_{i,e_1,t}$: Amount of unsatisfied demand of commodity type e_1 in affected area i at time t.

Modeling:

$$
\begin{aligned}
\min Z_1 = {} & \sum_m FixM_m \cdot ZM_m + \sum_l FixL_l \cdot ZL_l + \sum_p FixP_p \cdot ZP_p + \sum_g FixG_g \cdot ZG_g \\
& + \sum_{i,h,k_2,t} FixK_{k_2} \cdot X'_{i,h,t,k_2} + \sum_{i,m,k_2,t} FixK_{k_2} \cdot Y'_{i,m,t,k_2} \sum_{i,l,k_2,t} FixK_{k_2} \cdot Z'_{i,l,t,k_2} \\
& + \sum_{l,m,k_2,t} FixK_{k_2} \cdot U'_{m,l,t,k_2} + \sum_{m,h,k_2,t} FixK_{k_2} \cdot W'_{m,h,t,k_2} + \sum_{g,p,k_1,t} FixK_{k_1} \cdot N'_{g,p,t,k_1} \\
& + \sum_{p,i,k_1,t} FixK_{k_1} \cdot O'_{p,i,t,k_1} + \sum_{p,l,k_1,t} FixK_{k_1} \cdot Q'_{p,l,t,k_1} + \sum_{i,h,r_a,k_2,t} Trih_{i,h,k_2} \cdot X_{i,h,r_a,t,k_2} \\
& + \sum_{i,m,r_b,k_2,t} Trim_{i,m,k_2} \cdot Y_{i,m,r_b,t,k_2} + \sum_{i,l,r_c,k_2,t} Tril_{i,c,k_2} \cdot Z_{i,l,r_c,t,k_2} \\
& + \sum_{m,l,r_c,k_2,t} Trml_{m,l,k_2} \cdot U_{m,l,r_c,t,k_2} + \sum_{m,h,r_a,k_2,t} Trmh_{m,h,k_2} \cdot W_{m,h,r_a,t,k_2} \\
& + \sum_{g,p,e,k_1,t} Trgp_{g,p,k_1} \cdot N_{g,p,e,t,k_1} + \sum_{p,i,e_1,k_1,t} Tripi_{p,i,k-1} \cdot O_{p,i,e_1,t,k_1} \\
& + \sum_{p,l,e_2,k_1,t} Trpl_{p,l,k_1} \cdot Q_{p,l,e_2,t,k_1} \sum_{e_1,t} Hd_{e_1,t} \cdot In_{e_1,t}
\end{aligned} \tag{1}
$$

$$\min Z_2 = \omega \sum_{i,r,t} S1_{i,r,t} + (1-\omega) \sum_{i,e_1,t} S2_{i,e_1,t} \tag{2}$$

$$\min Z_3 = \sum_{k,t} No_{k,t} \tag{3}$$

$s.t:$

$$\sum_{h,k_2} X_{i,h,r_a,t,k_2} + \sum_{m,k_2} Y_{i,m,r_b,t,k_2} + \sum_{l,k_2} Z_{i,l,r_c,t,k_2} + \sum_{r} S1_{i,r,t} = \sum_{r} \tilde{D}_{\imath,r,t}, \qquad \forall i,t, \tag{4}$$

$$\sum_{p,k_1} O_{p,i,e_1,t,k_1} - In_{e_1,t} + In_{e_1,t-1} + S2_{i,e_1,t} = \widetilde{D2}_{i,e_1,t}, \qquad \forall i,e_1,t, \tag{5}$$

$$\sum_{p,k_1} Q_{p,l,e_2,t,k_1} = \widetilde{D3}_{l,e_2,t} \cdot ZL_l, \qquad \forall i,e_2,t, \tag{6}$$

$$\sum_{i,k_2} F_{m,R_b} \cdot Y_{i,m,r_b,t,k_2} = \sum_{l,k_2} U_{m,l,r_c,t,k_2}, \qquad \forall m,r,t, \tag{7}$$

$$\sum_{i,k_2} (1-F_{m,R_b}) \cdot Y_{i,m,r_b,t,k_2} = \sum_{h,k_2} W_{m,h,r_a,t,k_2}, \qquad \forall m,r,t, \tag{8}$$

$$\sum_{g,k_1} N_{g,p,e,t,k_1} = \sum_{i,k_1} O_{p,i,e_1,t,k_1} + \sum_{l,k_1} Q_{p,l,e_2,t,k_1}, \qquad \forall p,e,t, \tag{9}$$

$$\sum_{r_c,i,k_2} Z_{i,l,r_c,t,k_2} + \sum_{r_c,m,k_2} U_{m,l,r_c,t,k_2} \leq CapL_{l,t} \cdot ZL_l, \qquad \forall l,t, \tag{10}$$

$$\sum_{r_b,i,k_2} Y_{i,m,r_b,t,k_2} \leq CapM_{m,t} \cdot ZM_m, \qquad \forall m,t, \tag{11}$$

$$\sum_{r_a,i,k_2} X_{i,h,r_a,t,k_2} + \sum_{r_a,m,k_2} W_{m,h,r_a,t,k_2} \leq CapH_{h,t}, \qquad \forall h,t, \tag{12}$$

$$\sum_{g,k_1} N_{g,p,e,t,k_1} \leq CapP_{p,e,t} \cdot ZP_p, \qquad \forall p,e,t, \tag{13}$$

$$\sum_{p,k_1} N_{g,p,e,t,k_1} \leq CapG_{g,e,t} \cdot ZG_g, \qquad \forall g,e,t, \tag{14}$$

$$\begin{aligned} &\sum_{r_c,i,l} Z_{i,l,r_c,t,k_2} + \sum_{r_c,m,l} U_{m,l,r_c,t,k_2} + \sum_{r_b,i,m} Y_{i,m,r_b,t,k_2} + \sum_{r_a,i,h} X_{i,h,r_a,t,k_2} \\ &\quad + \sum_{r_a,m,h} W_{m,h,r_a,t,k_2} \leq \widetilde{Cap}_{k_2} \cdot No_{k_2,t}, \qquad \forall k_2,t, \end{aligned} \tag{15}$$

$$\sum_{e,g,p} N_{g,p,e,t,k_1} + \sum_{i,p,e_1} O_{p,i,e_1,t,k_1} + \sum_{p,l,e_2} Q_{p,l,e_2,t,k_1} \leq \widetilde{Cap}_{k_1} \cdot No_{k_1,t}, \qquad \forall k_1,t, \tag{16}$$

$$No_{k,t} \leq NT_{k,t}, \qquad \forall k,t, \tag{17}$$

$$\sum_{r_c} Z_{i,l,r_c,t,k_2} \leq BigM \cdot Z'_{i,l,t,k_2}, \qquad \forall i,l,t,k_2, \tag{18}$$

$$\sum_{r_c} U_{m,l,r_c,t,k_2} \leq BigM \cdot U'_{m,l,t,k_2}, \qquad \forall m,l,t,k_2, \tag{19}$$

$$\sum_{r_b} Y_{i,m,r_b,t,k_2} \leq BigM \cdot Y'_{i,m,t,k_2}, \forall i,m,t,k_2, \tag{20}$$

$$\sum_{r_a} X_{i,h,r_a,t,k_2} \leq BigM \cdot X'_{i,h,t,k_2}, \qquad \forall i,h,t,k_2, \tag{21}$$

$$\sum_{r_a} W_{m,h,r_a,t,k_2} \leq BigM \cdot W'_{m,h,t,k_2}, \qquad \forall m,h,t,k_2, \tag{22}$$

$$\sum_{e} N_{g,p,e,t,k_1} \leq BigM \cdot N'_{g,p,t,k_1}, \qquad \forall g,p,t,k_1, \tag{23}$$

$$\sum_{e_1} O_{p,i,r_1,t,k_1} \leq BigM \cdot O'_{p,i,t,k_1}, \qquad \forall p,i,t,k_1, \tag{24}$$

$$\sum_{e_2} Q_{p,l,r_1,t,k_1} \leq BigM \cdot Q'_{p,l,t,k_1}, \qquad \forall p,l,t,k_1, \tag{25}$$

$$\widetilde{Tuh}_{i,h,k_2} \cdot X'_{i,h,t,k_2} \leq Mtime1, \qquad \forall i,h,t,k_2, \tag{26}$$

$$\widetilde{Tum}_{i,m,k_2} \cdot Y'_{i,m,t,k_2} \leq Mtime1, \qquad \forall i,m,t,k_2, \tag{27}$$

$$\widetilde{Tmh}_{m,h,k_2} \cdot W'_{m,h,t,k_2} \leq Mtime1, \qquad \forall m,h,t,k_2, \tag{28}$$

$$\widetilde{Tgp}_{g,p,k_1} \cdot N'_{g,p,t,k_1} \leq Mtime2, \qquad \forall g,p,t,k_1, \tag{29}$$

$$\widetilde{Tpi}_{p,i,k_1} \cdot O'_{p,i,t,k_1} \leq Mtime2, \qquad \forall p,i,t,k_1, \tag{30}$$

$$\widetilde{Tpl}_{p,l,k_1} \cdot Q'_{p,l,t,k_1} \leq Mtime2, \qquad \forall p,l,t,k_1, \tag{31}$$

$$No_{k,t} \geq 0, \quad integer \tag{32}$$

$$\begin{aligned} &X_{i,h,r_a,t,k_2}, Y_{i,m,r_b,t,k_2}, Z_{i,m,r_b,t,k_2}, U_{m,l,r_c,t,k_2}, W_{m,h,r_a,t,k_2},\\ &O_{p,i,e_1,t,k_1}, Q_{p,l,e_2,t,k_1}, N_{g,p,e,t,k_1}, In_{e_1,t}, S1_{i,r,t}, S2_{i,e_1,t} \geq 0, \end{aligned} \tag{33}$$

$$\begin{aligned} &X'_{i,h,t,k_2}, Y'_{i,m,t,k_2}, Z'_{i,l,t,k_2}, W'_{m,h,t,k_2}, U'_{m,l,t,k_2}, O'_{p,i,t,k_1},\\ &Q'_{p,l,t,k_1}, N'_{g,p,t,k_1}, ZM_m, ZL_l, ZP_p, ZG_g \in \{0,1\}. \end{aligned} \tag{34}$$

Equation (1) shows the objective function of the problem and involves minimizing the total cost of the relief logistics network. Equation (2) is to minimize the missed estimation of the different items demand in damaged areas and the not-transferred injured people to other centers. Since the variables of the second objective function are not from the same domain, a weighted formula is used. Equation (3) minimizes the total number of cargo and relief vehicles at all times. Equation (4) shows the number of first, second, and third-class injured people transported by relief vehicles to hospitals, temporary medical centers, and temporary shelters. Equation (5) shows the amount of sent relief items from distribution centers to injured areas, along with its balance inventory. Equation (6) shows the rate of transferred critical items from distribution centers to temporary shelters. Equation (7) shows the number of second-class injured patients being treated in temporary medical centers and transferred to temporary shelters. Equation (8) shows the number of second-class injured patients who have not been treated in temporary medical centers but transferred to the hospital. Equation (9) shows the number of relief items transferred from the inventory to distribution centers and how they are distributed. Equations (10) to (14), respectively, show the restrictions related to the capacity of temporary shelters, temporary medical centers, hospitals, relief distribution centers, and supply centers after an incident. Equations (15) and (16) categorize the capacity of various cargo and relief vehicles into the required number of vehicles. Equation (17) ensures that the required number of cargo and relief vehicles do not exceed the number of available vehicles. Equations (18) to (25) are about existing limits related to cargo and relief vehicle routing among the relief logistics network. Equations (26) to (31) ensure that all vehicles assigned to each center transfer injured people and relief items to other centers within the allocated time. Equations (32) to (34) show the type and domain of the decision variables.

3.2 Uncertain parameters control

To make it functional, computational, and easy in computing, a triangular distribution is used to specify each fuzzy parameter. The distribution can be expressed as the degree of occurrence possibility for an event with uncertain characteristics. Figure 2 shows the distribution of the fuzzy parameter (C^p, C^m, C^0). C^0, C^m and C^p respectively represent the optimistic value, probable value, pessimistic value of fuzzy number $\tilde{C}$, which are determined by the decision-maker.

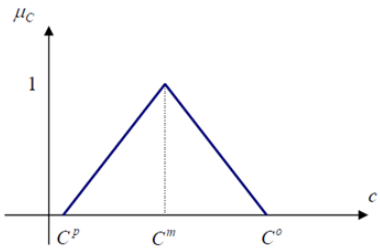

Figure 2: The triangular distribution of the fuzzy parameter $\tilde{C}$.

It should be noted that the probability distribution of fuzzy parameters is determined based on historical records, decision-maker subjective data knowledge. To defuzzify parameter $\tilde{C}$, Dotoli et al. (2017) method has been used [7]. Therefore, the defuzzified model of parameter $\tilde{C}$ will be as Equation (35).

$$C = w_1 C_\alpha^p + w_2 C_\alpha^m + w_3 C_\alpha^o. \tag{35}$$

In above equation

$$\begin{aligned} C_\alpha^p &= C^m + (1-\alpha)(C^p - C^m), \\ C_\alpha^m &= C^m, \\ C_\alpha^o &= C^o + \alpha(C^m - C^o). \end{aligned} \tag{36}$$

In Equation (36), α is the uncertainty rate (fit of alpha) and the values of $w_1 = w_3 = 1/6$ and $w_2 = 4/6$ are in accordance with (Liang, 2011) [12]. Therefore, the ultimate model is as follows. By considering the following uncertain parameters, the certain controlled model can be expressed by the fuzzy programming method as:

$$\begin{aligned} &\widetilde{D1}_{i,r,t} = (D1_{i,r,t}^p, D1_{i,r,t}^m, D1_{i,r,t}^o), \\ &\widetilde{D2}_{i,e_1,t} = (D2_{i,e_1,t}^p, D2_{i,e_1,t}^m, D2_{i,e_1,t}^o), \\ &\widetilde{D3}_{l,e_2,t} = (D3_{l,e_2,t}^p, D3_{l,e_2,t}^o). \\ &\widetilde{Tiih}_{i,h,k_2} = (Tiih_{i,h,k_2}^p, Tiih_{i,h,k_2}^m, Tiih_{i,h,k_2}^o), \end{aligned}$$

$$\widetilde{Tiim}_{i,m,k_2} = (Tiim^p_{i,m,k_2}, Tiim^m_{i,m,k_2}, Tiim^o_{i,m,k_2}),$$
$$\widetilde{Timh}_{m,h,k_2} = (Timh^p_{m,h,k_2}, Timh^m_{m,h,k_2}, Timh^o_{m,h,k_2}),$$
$$\widetilde{Tigp}_{g,p,k_1} = (Tigp^p_{g,p,k_1}, Tigp^m_{g,p,k_1}, Tigp^o_{g,p,k_1}),$$
$$\widetilde{Tipi}_{p,i,k_1} = (Tipi^p_{p,i,k_1}, Tipi^m_{p,i,k_1}, Tipi^o_{p,i,k_1}),$$
$$\widetilde{Tipl}_{p,l,k_1} = (Tipl^p_{p,l,k_1}, Tipl^m_{p,l,k_1}, Tipl^o_{p,l,k_1}),$$
$$\widetilde{Cap}_k = (Cap^p_k, Cap^m_k, Cap^o_k).$$

The certain supply chain model is expressed as follows:

$$\begin{aligned}
\min Z_1 = {} & \sum_m FixM_m \cdot ZM_m + \sum_l FixL_l \cdot ZL_l + \sum_p Fix\ P_p \cdot ZP_p + \sum_g FixG_g \cdot ZG_g \\
& + \sum_{i,h,k_2,t} FixK_{k_2} \cdot X'_{i,h,t,k_2} + \sum_{i,m,k_2,t} FixK_{k_2} \cdot Y'_{i,m,t,k_2} \sum_{i,l,k_2,t} FixK_{k_2} \cdot Z'_{i,l,t,k_2} \\
& + \sum_{l,m,k_2,t} FixK_{k_2} \cdot U'_{m,l,t,k_2} + \sum_{m,h,k_2,t} FixK_{k_2} \cdot W'_{m,h,t,k_2} + \sum_{g,p,k_1,t} FixK_{k_1} \cdot N'_{g,p,t,k_1} \\
& + \sum_{p,i,k_1,t} FixK_{k_1} \cdot O'_{p,i,t,k_1} + \sum_{p,l,k_1,t} FixK_{k_1} \cdot Q'_{p,l,t,k_1} + \sum_{i,h,r_a,k_2,t} Trih_{i,h,k_2} \cdot X_{i,h,r_a,t,k_2} \\
& + \sum_{i,m,r_b,k_2,t} Trim_{i,m,k_2} \cdot Y_{i,m,r_b,t,k_2} + \sum_{i,l,r_c,k_2,t} Tril_{i,c,k_2} \cdot Z_{i,l,r_c,t,k_2} \\
& + \sum_{m,l,r_c,k_2,t} Trml_{m,l,k_2} \cdot U_{m,l,r_c,t,k_2} + \sum_{m,h,r_a,k_2,t} Trmh_{m,h,k_2} \cdot W_{m,h,r_a,t,k_2} \\
& + \sum_{g,p,e,k_1,t} Trgp_{g,p,k_1} \cdot N_{g,p,e,t,k_1} + \sum_{p,i,e_1,k_1,t} Trpi_{p,i,k_1} O_{p,i,e_1,t,k_1} \\
& + \sum_{p,l,e_2,k_1,t} Trpl_{p,l,k_1} \cdot Q_{p,l,e_2,t,k_1} \sum_{e_1,t} Hd_{e_1,t} \cdot In_{e_1,t}
\end{aligned} \tag{37}$$

$$\min Z_2 = \omega \sum_{i,r,t} S1_{i,r,t} + (1-\omega) \sum_{i,e_1,t} S2_{i,e_1,t} \tag{38}$$

$$\min Z_3 = \sum_{k,t} No_{k,t} \tag{39}$$

s.t

$$\sum_{h,k_2} X_{i,h,r_a,t,k_2} + \sum_{m,k_2} Y_{i,m,r_b,t,k_2} + \sum_{l,k_2} Z_{i,l,r_c,t,k_2} + \sum_r S1_{i,r,t} = \sum_r \begin{pmatrix} w_1 D1^{\alpha,p}_{i,r,t} + w_2 D1^{\alpha,m}_{i,r,t} \\ +w_1 D1^{\alpha,t}_{i,r,t} \end{pmatrix}, \forall i,t, \tag{40}$$

$$\sum_{p,k_1} O_{p,i,e_1,t,k_1} - In_{e_1,t} + In_{e_1,t-1} + S2_{i,e_1,t} = \begin{pmatrix} w_1 D2^{\alpha,p}_{i,e_1,t} + w_2 D2^{\alpha,m}_{i,e_1,t} \\ +w_3 D2^{\alpha,O}_{i,e_1,t} \end{pmatrix}, \forall i, e_1, t, \tag{41}$$

$$\sum_{p,k_1} Q_{p,l,e_2,t,k_1} = \left(w_1 D3^{\alpha,p}_{l,e_2,t} + w_2 D3^{\alpha,m}_{l,e_2,t} + w_3 D3^{\alpha,O}_{l,e_2,t}\right), \forall i, e_2, t, \tag{42}$$

$$\begin{aligned}
& \sum_{r_c,i,l} Z_{i,l,r_c,t,k_2} + \sum_{r_c,m,l} U_{m,l,r_c,t,k_2} + \sum_{r_b,i,m} Y_{i,m,r_b,t,k_2} + \sum_{r_a,i,h} X_{i,h,r_a,t,k_2} \\
& + \sum_{r_a,m,h} W_{m,h,r_a,t,k_2} \leq \begin{pmatrix} w_1 CapK^{\alpha,p}_{k_2} + w_2 CapK^{\alpha,m}_{k_2} \\ +w_3 CapK^{\alpha,O}_{k_2} \end{pmatrix} \cdot No_{k_2,t}, \forall k_2, t,
\end{aligned} \tag{43}$$

$$\sum_{e,g,p} N_{g,p,e,t,k_1} + \sum_{i,p,e_1} O_{p,i,e_1,t,k_1} + \sum_{p,l,e_2} Q_{p,l,e_2,t,k_1} \leq$$

$$(w_1 CapK_{k_1}^{\alpha,p} + w_2 CapK_{k_1}^{\alpha,m} + w_3 CapK_{k_1}^{\alpha,o}) \cdot No_{k_1,t}, \ \forall k_1, t, \tag{44}$$

$$\left(w_1 Tiih_{i,h,k_2}^{\alpha,p} + w_2 Tiih_{i,h,k_2}^{\alpha,m} + w_3 Tiih_{i,h,k_2}\right) \cdot X'_{i,h,t,k_2} \le Mtime1, \ \forall i,h,t,k_2, \tag{45}$$

$$\left(w_1 Tiih_{i,m,k_2}^{\alpha,p} + w_2 Tiim_{i,m,k_2}^{\alpha,m} + w_3 Tiim_{i,m,k_2}\right) \cdot Y'_{i,m,t,k_2} \le Mtime1, \ \forall i,m,t,k_2, \tag{46}$$

$$\left(w_1 Timh_{m,h,k_2}^{\alpha,p} + w_2 Timh_{m,h,k_2}^{\alpha,m} + w_3 Timh_{m,h,k_2}\right) \cdot W'_{m,h,t,k_2} \le Mtime1, \ \forall m,h,t,k_2, \tag{47}$$

$$\left(w_1 Tigp_{g,p,k_1}^{\alpha,p} + w_2 Tigp_{g,p,k_1}^{\alpha,m} + w_3 Tigp_{g,pk_1}^{\alpha,o}\right) \cdot N'_{g,p,tk_1} \le Mtime2, \ \forall g,p,t,k_1, \tag{48}$$

$$\left(w_1 Tipi_{p,i,k_1}^{\alpha,p} + w_2 Tipi_{p,i,k_1}^{\alpha,m} + w_3 Tipi_{p,i,k_1}^{\alpha,o}\right) \cdot O'_{p,i,t,k_1} \le Mtime2, \ \forall p,i,t,k_1, \tag{49}$$

$$\left(w_1 Tipl_{p,l,k_1}^{\alpha,p} + w_2 Tipl_{p,l,k_1}^{\alpha,m} + w_3 Tipl_{p,l,k_1}^{\alpha,o}\right) \cdot Q'_{p,l,t,k_1} \le Mtime2, \ \forall p,l,t,k_1, \tag{50}$$

$$\begin{cases} D1_{i,r,t}^{\alpha,p} = D1_{i,r,t}^{m} + (1-\alpha)(D1_{i,r,t}^{p} - D1_{i,r,t}^{m}) \\ D1_{i,r,t}^{\alpha,m} = D1_{i,r,t}^{m}, \qquad \forall i,r,t \\ D1_{i,r,t}^{\alpha,o} = D1_{i,r,t}^{o} + (\alpha)(D1_{i,r,t}^{m} - D1_{i,r,t}^{o}) \end{cases} \tag{51}$$

$$\begin{cases} D2_{i,e_1,t}^{\alpha,p} = D2_{i,e_1,t}^{m} + (1-\alpha)(D2_{i,e_1,t}^{p} - D2_{i,e_1,t}^{m}) \\ D2_{i,e_1,t}^{\alpha,m} = D2_{i,e_1,t}^{m}, \qquad \forall i,e_1,t \\ D2_{i,e_1,t}^{\alpha,o} = D2_{i,e_1,t}^{o} + (\alpha)(D2_{i,e_1,t}^{m} - D2_{i,e_1,t}^{o}) \end{cases} \tag{52}$$

$$\begin{cases} D3_{l,e_2,t}^{\alpha,p} = D3_{l,e_2,t}^{m} + (1-\alpha)(D3_{i,e_2,t}^{p} - D3_{l,e_2,t}^{m}) \\ D3_{l,e_2,t}^{\alpha,m} = D3_{l,e_2,t}^{m}, \qquad \forall l,e_2,t^m \\ D3_{l,e_2,t}^{\alpha,o} = D3_{l,e_2,t}^{o} + (\alpha)(D3_{i,e_2,t}^{m} - D3_{l,e_2,t}^{o}) \end{cases} \tag{53}$$

$$\begin{cases} CapK_{k}^{\alpha,p} = CapK_{k}^{m} + (1-\alpha)(CapK_{k}^{p} - CapK_{k}^{m}) \\ CapK_{k}^{\alpha,m} = CapK_{k}^{m}, \qquad \forall k \\ CapK_{k}^{\alpha,o} = CapK_{k}^{o} + (\alpha)(CapK_{k}^{m} - CapK_{k}^{o}) \end{cases} \tag{54}$$

$$\begin{cases} Tiih_{i,h,k_2}^{\alpha,p} = Tiih_{i,h,k_2}^{m} + (1-\alpha)(Tiih_{i,h,k_2}^{p} - Tiih_{i,h,k_2}^{m}) \\ Tiih_{i,h,k_2}^{\alpha,m} = Tiih_{i,h,k_2}^{m}, \qquad \forall i,h,k_2 \\ Tiih_{i,h,k_2}^{\alpha,o} = Tiih_{i,h,k_2}^{o} + (\alpha)(Tiih_{i,h,k_2}^{m} - Tiih_{i,h,k_2}^{o}) \end{cases} \tag{55}$$

$$\begin{cases} Tiim_{i,m,k_2}^{\alpha,p} = Tiim_{i,m,k_2}^{m} + (1-\alpha)(Tiim_{i,m,k_2}^{p} - Tiim_{i,m,k_2}^{m}) \\ Tiim_{i,m,k_2}^{\alpha,m} = Tiim_{i,m,k_2}^{m}, \qquad \forall i,m,k_2 \\ Tiim_{i,m,k_2}^{\alpha,o} = Tiim_{i,m,k_2}^{o} + (\alpha)(Tiim_{i,m,k_2}^{m} - Tiim_{i,m,k_2}^{o}) \end{cases} \tag{56}$$

$$\begin{cases} Timh_{m,h,k_2}^{\alpha,p} = Timh_{m,h,k_2}^{m} + (1-\alpha)(Timh_{m,h,k_2}^{p} - Timh_{m,h,k_2}^{m}) \\ Timh_{m,h,k_2}^{\alpha,m} = Timh_{m,h,k_2}^{m}, \qquad \forall m,h,k_2 \\ Timh_{m,h,k_2}^{\alpha,o} = Timh_{m,h,k_2}^{o} + (\alpha)(Timh_{m,h,k_2}^{m} - Timh_{m,h,k_2}^{o}) \end{cases} \tag{57}$$

$$\begin{cases} Tigp_{g,p,k_1}^{\alpha,p} = Tigp_{g,p,k_1}^{m} + (1-\alpha)(Tigp_{g,p,k_1}^{p} - Tigp_{g,p,k_1}^{m}) \\ Tigp_{g,p,k_1}^{\alpha,m} = Tigp_{g,p,k_1}^{m}, \qquad \forall g,p,k_1 \\ Tigp_{g,p,k_1}^{\alpha,o} = Tigp_{g,p,k_1}^{o} + (\alpha)(Tigp_{g,p,k_1}^{m} - Tigp_{g,p,k_1}^{o}) \end{cases} \tag{58}$$

$$\begin{cases} Tipi_{p,i,k_1}^{\alpha,p} = Tipi_{p,i,k_1}^{m} + (1-\alpha)(Tipi_{p,i,k_1}^{p} - Tipi_{p,i,k_1}^{m}) \\ Tipi_{p,i,k_1}^{\alpha,m} = Tipi_{p,i,k_1}^{m}, \qquad \forall g,p,k_1 \\ Tipi_{p,i,k_1}^{\alpha,o} = Tipi_{p,i,k_1}^{o} + (\alpha)(Tipi_{p,i,k_1}^{m} - Tipi_{p,i,k_1}^{o}) \end{cases} \tag{59}$$

$$\begin{cases} Tipl_{p,l,k_1}^{\alpha,p} = Tipl_{p,l,k_1}^{m} + (1-\alpha)(Tipl_{p,l,k_1}^{p} - Tipl_{p,l,k_1}^{m}) \\ Tipl_{p,l,k_1}^{\alpha,m} = Tipl_{p,l,k_1}^{m}, \qquad \forall p,l,k_1 \\ Tipl_{p,l,k_1}^{\alpha,o} = Tipl_{p,l,k_1}^{o} + (\alpha)(Tipl_{p,l,k_1}^{m} - Tipl_{p,l,k_1}^{o}) \end{cases} \tag{60}$$

$$(7)-(14),(17)-(25),(32)-(34) \tag{61}$$

4 Solving Methods

In this paper, due to the NP-hardness of the problem, the NSGA-II and MOPSO algorithms are used to solve the relief logistics problem. Therefore, in this section, the basic principles of the mentioned algorithms are discussed. In the end, we introduce indexes to compare the efficient responses of each algorithm.

4.1 Non-dominated sorting genetic algorithm - II

This algorithm, like the genetic algorithm, begins with a randomly generated primitive population. In the next step, the generated population is evaluated from the viewpoint of the defined objective functions (suppose we have two minimization goal functions). After dividing the population into different categories using the non-dominated sorting process, we calculate the control parameter called the crowding distance. This parameter is calculated for each of two members in each group and represents a measure of the proximity of the target member to the other members of that group. A large amount of this parameter will lead to divergence and a wider range of population members. On the other hand, in this algorithm, among the answers of each generation P_t, some of them are selected using the binary tournament selection method. In the binary selection method, two random responses are selected from the population, and then a comparison is made between the two answers, so the best one is eventually selected. The selection criteria in NSGA-II are primarily the response rank and, secondly, the crowding distance which is related to the answer. The lowest response rank and the highest crowding distance are preferred. By repeating the binary selection on the population of each generation, a set of individuals of that generation is selected to participate in the combination and mutation. The combination function is performed on the part of the selected individuals, and the mutation function is carried out on the rest. As a result, the population Q_t is made up of children and mutated individuals. Subsequently, this population is merged with the main population. The members of the newly formed population R_t are sorted based on their rank in ascending order. Members of the same ranked, are sorted based on crowding distance in descending order. At present, population members are sorted primarily based on their rank and secondly based on crowding distance. Equal to the number of people in the main population P_{t+1} members are selected from the top of the sorted list, and the rest of the members are discarded. Selected members from the next generation population, and the cycle in this section is often called the Pareto Front. None of the answers in the Pareto front are superior to each other and, depending on the circumstances, all of them can be considered as an optimal decision.

4.2 Multi-objective particles swarm optimization algorithm

Moore and Chapman (1999) developed the optimization of particle swarm for multi-objective problems [13]. Coello, et. al., in 2009 proposed an algorithm based on the

idea of an external archive [6]. Also, to select the leader, the target space is tabled. This method is described in detail in this article. To solve multi-objective problems by particle swarm optimization algorithm, it is evident that the general scheme of this algorithm needs to be modified. The primary goals while solving a multi-objective problem to achieve the maximization of the number of elements of the Pareto optimal set found, minimization of the distance of the Pareto front produced by algorithm along with maximization of the spread of solutions found. The general process of the MOPSO algorithm is described in the following steps [9]:
Step one: Create a Primary Population
Step Two: Separate nondominated members of the population and save them in archives or foreign reservoirs
Step Three: Tabling target discovered space
Step Four: Each particle chooses one leader from the archives.
Step Five: Update the velocity and position of the particles.
Each particle contains information that includes the best value so far (personal best) and the position of X^t. This information is the result of comparing the efforts that each particle makes to find the best answer. Each particle also finds the best answer so far received in the whole group, comparing the optimal values of various particles (global best). Each particle tries to change its position using the following information to achieve the best answer: 1. X^t current position, 2. V^t current velocity, 3. distance between the current and optimal personal position, and 4. distance between the current position and Pervasive optimum. Thus, the velocity of each particle and, consequently, its new position are expressed in terms of Equations (62) and (63).

$$V_i^{t+1} = wV_i^t + c_1 rand(pbest_i - X_i^t) + c_2 rand(gbest_i - X_i^t), \tag{62}$$

$$X_i^{t+1} = X_i^t + V_i^{t+1}. \tag{63}$$

In the above equation, V_i^{t+1} is the velocity of the particle i in the new repetition t, V_i^t is the velocity of the particle i in the current repetition t, X_i^t is the current position of the particle $t+1$, X_i^{t+1} is the position of the particle in the new repetition. $pbest_i$ is the best position that particle i has ever had, and $gbest_i$ is the best position of the best particle (the best position that all the particles have ever taken). $Rand$ is a random number between zero and one that is used to preserve the variety and diversity of the group. c_1 and c_2 are cognitive and social parameters, respectively. Choosing the appropriate value for these parameters will accelerate the convergence of the algorithm and prevent early convergence in local optimizations. Recent research suggests that choosing a larger value for a cognitive parameter c_1 is more appropriate than the social parameter c_2 (Khan, S. et al., 2018) [11]. The parameter w is the weighted inertia used to ensure convergence in the particle group. Weight inertia is used to control the effect of previous velocity records on current velocities.
Step 6: Use the mutation operator
Step 7: The best personal memory of each particle is updated.
Step 8: Add new nondominated members to the archive and delete the dominated members.
Step 9: Update the tabulation.

Step 10: If the stop condition is met, the algorithm stops, and the best particle among the crowd is the answer given to the problem. Otherwise, go to step four.

4.3 Multi-objective meta-heuristics algorithms comparison indices

Indicators are presented below to compare which algorithm is more applicable than another. Suppose the set of effective responses is as follows:

Most Expansion Index (MSI)

This criterion measures the expansion of the space for efficient responses. The more efficient the answers are in a wider space, the larger is the index, so the higher values of this index are intended. Suppose
f_j^{max} : The maximum value of the objective function for the purpose j among efficient responses.
f_j^{min} : The minimum value of the objective function for the purpose j among efficient responses.
This index is indicated as D and is calculated using Equation (64).

$$D = \sqrt{\sum_{j=1}^{k} (f_j^{max} - f_j^{min})^2}. \tag{64}$$

The Number of Effective responses or Pareto index (NPF)
This index indicates the number of effective responses that can be extracted using the model. Obviously, higher values for this index are preferred.

Model runtime (CPU-time)
This index shows the runtime of the model to achieve efficient responses. Obviously, the lower values for this index are preferred.

Metric Distance Index (SM)
By using this index, we will measure the uniformity of non-dominated solutions. The lower values for this index are preferred.
is calculated from Equations (65) and (66):

$$d_i = \min_{\substack{j=1,\dots,n \\ j\neq i}} \left(\sum_{k=1}^{3} |f_k^i - f_k^j| \right), \qquad i = 1,\dots,n, \tag{65}$$

$$SM = \frac{\sum_{i=1}^{n-1} |\bar{d} - d_i|}{(n-1)\bar{d}}. \tag{66}$$

5 Computational Results

5.1 Solving small sample problems by ϵ-constraint method

In this section, first, to examine the model as well as its verification, a small sample size problem is considered in accordance with the size given in Table 1. The certain and uncertain parameters considered are also generated using a uniform distribution function, based on Tables 2 and 3, to solve the problem.

Table 1: Small sample problem.

Set	Size	Set	Size
I	6	K_1	4
L	4	K_2	4
M	5	K	8
P	4	R	3
H	3	E_1	2
G	4	E_2	2
T	2	E	4

Table 2: The certain parameters are generated using a uniform distribution function.

Parameter	Interval	Parameter	Interval
$Trih_{i,h,k_2}$	$U \sim (5,10)$	$CapL_{l,t}$	$U \sim (400,450)$
$Trim_{i,m,k_2}$	$U \sim (5,10)$	$CapM_{m,t}$	$U \sim (400,450)$
$Trmh_{m,h,k_2}$	$U \sim (5,10)$	$CapH_{h,t}$	$U \sim (400,450)$
$Tril_{i,l,k_2}$	$U \sim (5,10)$	$CapG_{g,e,t}$	$U \sim (100,120)$
$Trml_{m,l,k_2}$	$U \sim (5,10)$	$CapP_{p,e,t}$	$U \sim (100,120)$
$Trgp_{g,p,k_1}$	$U \sim (5,10)$	$FixL_l$	$U \sim (50000,100000)$
$Trpi_{p,i,k_1}$	$U \sim (5,10)$	$FixM_m$	$U \sim (50000,100000)$
$Trpl_{p,l,k_1}$	$U \sim (5,10)$	$FixG_g$	$U \sim (50000,100000)$
$Hd_{e_1,t}$	$U \sim (1,3)$	$F-xP_p$	$U \sim (50000,100000)$
$NT_{k,t}$	$U \sim (10,15)$	$FixK_k$	$U \sim (100,200)$
F_{m,R_b}	$U \sim (4,5)/10$	$BigM$	10000
$Mtime1$	20	$Mtime2$	20

First and foremost, before solving the small sample problem with the ϵ-constraint method, the best and worst amount of each target function is calculated using the single optimization method. In this method, each objective function is solved, regardless of other objective functions, by using the GAMS software to determine the upper and lower boundary of each target. Therefore, it can be concluded that the generated effective responses should be between the upper and lower boundary of each target function (the best and worst values of each objective function). Table 4, named the $Payoff$ table, presents the best and worst value of each objective.

Table 3: The certain parameters are generated using a uniform distribution function.

Parameter	Pessimistic value	Most likely	Optimistic value
$\widetilde{D1}_{i,r,t}$	$U*10 \sim (20,30)$	$U*10 \sim (10,20)$	$U*10 \sim (5,10)$
$\widetilde{D2}_{i,e_1,t}$	$U \sim (70,80)$	$U \sim (60,70)$	$U \sim (50,60)$
$\widetilde{D3}_{l,e_2,t}$	$U \sim (80,90)$	$U \sim (70,80)$	$U \sim (80,90)$
$\widetilde{T\iota h}_{i,h,k_2}$	$U \sim (25,30)$	$U \sim (15,25)$	$U \sim (10,15)$
$\widetilde{T\iota m}_{i,m,k_2}$	$U \sim (25,30)$	$U \sim (15,25)$	$U \sim (10,15)$
$\widetilde{T\iota mh}_{m,h,k_2}$	$U \sim (25,30)$	$U \sim (15,25)$	$U \sim (10,15)$
$\widetilde{T\iota gp}_{g,p,k_1}$	$U \sim (25,30)$	$U \sim (15,25)$	$U \sim (10,15)$
$\widetilde{T\iota p\iota}_{p,i,k_1}$	$U \sim (25,30)$	$U \sim (15,25)$	$U \sim (10,15)$
$\widetilde{T\iota pl}_{p,l,k_1}$	$U \sim (25,30)$	$U \sim (15,25)$	$U \sim (10,15)$
$\widetilde{Cap}_k$	$U \sim (50,55)$	$U \sim (45,50)$	$U \sim (40,45)$

Table 4: Payoff table associated with solving a small sample problem with an ϵ-constraint method.

Payoff	Z_1	Z_2	Z_3
Z_1	554028.56	4081.25	892
Z_2	1240001.14	2276.45	892
Z_3	1225043.01	4030.50	97

According to the $Payoff$ table, the best value of the first objective function is 544028.56, the best value of the second objective function is 2276.45 and the best value of the third objective function 97. Therefore, the result can be that a set of effective responses cannot provide better answers than the above. Thus, Table 5 shows the set of efficient answers from solving the small-sample sample problem by ϵ-constraint approach in the alpha-fit of 0.5.

Table 5: Set of efficient answers from solving the small-sample sample problem by ϵ-constraint method.

Efficient answer	Z_1	Z_2	Z_3
1	552568.52	2924.08	122
2	552491.45	2948.41	121
3	552401.41	2983.25	120
4	552371.14	3021.41	118
5	551604.61	3068.16	117
6	551156.80	3114.91	116
7	550809.50	3161.66	115
8	549839.27	3301.91	112
9	549093.07	3492.12	108
10	547738.31	3629.16	105
11	547293.80	3722.66	103
12	546478.20	3862.91	100
13	545933.28	4003.16	97

According to Table 5, 13 various effective answers are derived from the ϵ-constraint method for the small-sample problem

5.2 Solving small-size sample problems by meta-heuristic algorithms

In this section, due to the complexity of the problem and its NP-hardness, NSGA-II and MOPSO Meta-Heuristic Algorithms have been used to solve larger size sample problems. Therefore, in order to determine the coding accuracy, the small size sample problem presented in Table 1 has been considered and the problem has been solved by mentioned algorithms to determine the difference between the objectives functions of the meta- Heuristic algorithms and the ϵ-constraint method. Before solving the problem and analyzing the results, the initial parameters of the NSGA-II and MOPSO algorithms were adjusted by the Taguchi method. Tables 6 and 7 show the proposed levels of the parameters of these algorithms and the optimal value of each parameter obtained by theTaguchi method.

Table 6: Value of adjusted parameters (optimized) for NSGA-II.

Algorithm	Parameter	Level1	Level2	Level3	Optimized
NSGA-II	Maximum number of repetitions	50	100	200	200
	Population	50	100	200	100
	Combination rate	0.3	0.5	0.7	0.3
	Mutation rate	0.3	0.5	0.7	0.7

Table 7: Value of adjusted parameters (optimized) for the MOPSO.

Algorithm	Parameter	Level 1	Level 2	Level 3	Optimized
MOPSO	Maximum number of repetitions	50	100	200	200
	Particles	50	100	200	50
	Initial velocity coefficient	1	1.5	2	2
	Secondary velocity coefficient	1	1.5	2	1.5
	Gravity coefficient	0.8	0.9	1	0.9

After adjusting the parameters of the meta-heuristics algorithms, the small-size sample presented in Table 1 is again solved by the proposed algorithms.

After solving the small sample problem with the NSGA-II and the MOPSO algorithms, 23 effective responses for the NSGA-II algorithm and 17 effective responses for the MOPSO algorithm were obtained. According to these tables, with the increase in the number of relief and cargo vehicles, the total cost of the supply chain network design is increased and, consequently, due to the transfer of more injured to medical centers, etc., the amount of shortage or lack of service to the injured people is reduced. After solving the small size problem with different methods, for the purpose of evaluating the effective response indicators, Table 8 is created. In this table, the averages of the target functions, the number of efficient responses, the most expansion index, the metric distance index, and the computation time are considered.

Table 8: Comparison of the indicators of the affective responses is the solving of the small size problem.

	Solving methods		
Indexes	MOPSO	NSGA-II	GAMS(ϵ-constraint)
Mean of Z_1	621766.78	624332.30	549983.02
Mean of Z_2	2732.39	2786.55	3325.67
Mean of Z_3	127.82	123.82	111.84
NPF	17	23	13
MSI	111452.59	188440.97	6277.45
SM	0.79	0.78	0.546
CPU-Time	67.31	58.39	267.16

According to Table 8, it can be concluded that if one specific problem-solving method has the lowest values in the index of target functions averages, the metric distance, and the computation time, and has the higher values in the number of effective responses index and the distance index, the most efficient solution method is obtained. By examining the results of Table 8, the ϵ-constraint method is better than other methods in the indexes of the average of the first and third objective functions and the metric distance index. The NSGA-II algorithm has been better in acquiring the number of efficient responses, the most extension, and computation time indexes, and the MOPSO algorithm has also been better considering the mean index of the second-objective function.

5.3 Solving larger size problems

In this section, due to the inadequacy of the GAMS software and the ϵ-constraint method to solving relief logistics problems, only the NSGA-II and MOPSO algorithms are used to solve the problem in larger sizes. In this section, the large sample problems have been reviewed at three levels: small, medium, and large. Therefore, 15 sample problems are designed based on Table 9 and generated data according to Tables 2 and 3.

Table 9: The large sample size problems.

Set	Sample Problems														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
I	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
L	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
M	10	10	12	12	14	14	16	16	18	18	20	20	22	25	25
P	6	6	6	6	8	8	8	8	10	10	10	10	12	12	12
H	4	4	4	4	4	6	6	6	6	8	8	8	8	12	12
G	6	6	6	6	8	8	8	8	10	10	10	12	12	12	12
T	2	2	2	3	3	3	4	4	4	5	5	5	6	6	6
K_1	6	6	6	6	8	8	8	8	10	10	10	12	12	12	12
K_2	6	6	6	6	8	8	8	8	10	10	10	12	12	12	12
K	12	12	12	12	16	16	16	16	20	20	20	24	24	24	24
R	4	4	4	4	5	5	5	6	6	6	6	7	7	7	8
E_1	3	3	3	3	3	4	4	4	4	5	5	5	6	6	6
E_2	3	3	3	3	3	4	4	4	4	5	5	5	6	6	6
E	6	6	6	6	6	8	8	8	8	10	10	10	12	12	12

In this section, sample problems from 1 to 15 are reviewed. As stated, the data used to solve these problems is taken from Tables 2 and 3. In addition to this information, in all of the problems examined, the alpha fitting level is assumed to be 0.5. Table 10 shows the average of the effective responses and comparison indicators of the meta-heuristics algorithms for the solving of larger sample size problems.

T-test was used at 95% confidence level to examine the significant difference between the obtained averages in different indices in solving larger sample size problems. Therefore, considering the confidence level if the P test statistic is less than 0.05, there is a significant difference between the mean of that computational index. On the other hand, if the value of P test is more than 0.05, there is no significant difference between the computing index averages. Table 11 summarizes the results of the T-test test among the averages of the indices used in Table 11 for larger sample size problems.

Regarding the value of the P test obtained from Table 11, it can be concluded that there is no significant difference between any of the averages of the studied indices in larger sample size problems. Therefore, the multi-objective multi-factor TOPSIS decision-making method has been used to conclude on the most efficient algorithm in solving sample size larger. Table 12 summarizes the results of the indexes obtained from solving sample problems by the larger size and the amount of utility weight. Obviously, the greater the weight of the utility, the higher the efficiency of the algorithm in solving the larger sample problem, considering all the indices.

According to Table 12, the NSGA-II algorithm is more efficient than the MOPSO algorithm with a larger utility weight (0.8054) in solving larger size sample problems considering all comparison criteria.

Table 10: Comparison of multi-objective multi-heuristic algorithms indicators in solving larger-size problems.

Method	Problem	Mean of Z_1	Mean of Z_2	Mean of Z_3	SM	MSI	NPF	CPU Time
NSGA-II	1	814624.5	4034.91	212.0	0.37	270273.91	19	66.64
	2	893903.9	4037.42	250.2	0.77	585593.25	19	109.5
	3	1054091.5	4499.47	305.6	0.7	479316.63	20	173.8
	4	1340197.5	6188.69	554.4	0.57	850298.87	14	244.0
	5	1499104.9	7570.90	613.0	0.41	1290789.7	14	332.4
	6	1819457.7	10908.06	1115.2	0.67	2508017.5	26	432.4
	7	11904795.9	13175.46	1199.2	0.52	2797218.3	24	543.0
	8	2147039.9	14072.13	1318.8	0.48	2526486.4	19	661.9
	9	2275232.2	14799.79	1376.8	0.85	2489246.8	19	814.0
	10	2821578.6	20513.16	2191.6	0.39	350950.3	23	956.4
	11	2977894.9	21975.99	2315.00	0.76	3087180.76	26	1039
	12	3196969.1	24808.73	2470.40	0.45	4883033.12	27	1324
	13	3869518.3	33011.01	3557.80	0.97	3839428	32	1530
	14	4233689.6	34484.42	3725.60	1.03	4565022.62	29	1807
	15	4451831.3	36058.92	3939.00	0.68	5381370.91	27	2640
MOPSO	1	821831.2	3944.16	207.8	0.46	109850.13	18	75.39
	2	922036.1	4152.08	246.4	0.62	329845.53	14	90.49
	3	1055897.5	4493.01	296.8	0.23	370471.43	18	111.8
	4	1334944.5	6423.04	543.0	0.59	463108.57	16	133.3
	5	1513069.6	7370.91	625.4	0.35	817523.73	18	261.6
	6	1837999.3	11194.19	1096.6	0.55	2008648.7	31	345.4
	7	1922322.9	12984.41	1181.0	0.59	2559860.1	28	494.9
	8	2109015.3	13969.09	1294.4	0.84	3694417.3	19	723.4
	9	2259144.9	14816.02	1375.8	0.69	2215210.1	15	982.0
	10	2835361.1	20534.23	2167.4	0.36	2437807.6	25	1326
	11	2979000.7	21726.00	2308.00	0.94	2437807.91	32	1325
	12	3204856.4	24920.01	2463.80	0.86	3887334.58	19	1834
	13	3865944.8	3293.58	3556.20	0.36	3757576.16	24	2340
	14	4244230.4	34458.61	3660.40	0.47	4595983.26	21	2978
	15	4459728.0	36441.11	3925.60	1.03	5928298.63	20	3953

Table 11: Statistical T-test results at 95% confidence level for the indexes in larger-size problems.

Index	Mean difference	Lower bound	Upper bound	P	T
Z_1	4364	−891413	900140	0.992	0.01
Z_2	15	−8455	8485	0.997	0.01
Z_3	13	−952	978	0.978	0.03
NPF	1.33	−2.77	5.44	0.511	0.67
MSI	230699	−1046492	1507890	0.714	0.37
SM	0.045	−0.1222	0.2128	0.583	0.56
CPU-Time	287	−455	1029	0.432	0.80

Table 12: The most effective meta-heuristic algorithm for solving sample problems of larger size.

Algorithm	$Z1$	$Z2$	$Z3$	SM	MSI	NPF	CPU-Time	Utility weight
NSGA-II	2353329	16675.94	1676.30	0.641	2604948	22.53	844.816	0.8054
MOPSO	2357629	16690.83	1663.24	0.596	2374250	21.20	1131.61	0.1946
Index weight	0.2	0.2	0.2	0.1	0.1	0.1	0.1	

6 Conclusions and Suggestions for Future Studies

This paper presents a multi-objective model for the multi-period location-routing problem, taking into account the evacuation of casualties and homeless people and fuzzy paths in relief logistics. First, an uncertain multi-objective model of the problem was designed under uncertain parameters of demand, time, and transport capacity, and then, using the fuzzy programming method, uncertain parameters of the problem were controlled. Considering the multi-purpose design of the model, a small sample size was first designed, and the model was solved using the ϵ-constraint method in GAMS software, resulting in 13 different efficient responses. Then, due to the NP-hardness of the problem and the inability of GAMS software to solve the model in larger sizes NSGA-II and MOPSO meta-heuristic algorithms were used to solve the problem. At first, the small sample size problem solved by the GAMS software was solved by these algorithms, which showed the high efficiency of the algorithms in obtaining efficient responses. Then, 15 sample problems were designed in larger sizes, and sample problems were analyzed in 5 successive replications by the NSGA-II and MOPSO algorithms. Before solving sample problems in larger sizes, the initial parameters of both algorithms were adjusted by the Taguchi method so that the algorithms have the highest efficiency in obtaining results. The results showed that there was no significant difference between all indices of the case. The indexes computed in this problem include the mean of target functions, the number of efficient responses, the most exponential index, the metric distance index, and computational time. Due to the lack of decision about choosing the most efficient algorithm, the TOPSIS multi-criteria decision-making method was used, which resulted in the selection of the NSGA-II algorithm with a utility weight of

0.8054 compared to the MOPSO algorithm with a utility weight of 0.1946 in solving all sample problems. In this regard, the followings are suggestions for other researchers:

1. Considering the transportation cost parameter to be uncertain.
2. Using robust fuzzy optimization method to control uncertain parameters due to lack of access to historical data
3. Use of other meta-heuristic algorithms such as MOSA, MOALO to solve problems
4. We were considering the reliable objective function along with the mentioned target functions in this study.

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