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Solving a new bi-objective model for relief logistics in a humanitarian supply chain using bi-objective meta-heuristic algorithms

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Abstract. One of the most important factors in a humanitarian supply chain during a disaster is a timely and efficient response. Delivering emergency commodities to the affected areas is also of significance in reducing consequences. Moreover, transferring the injured people in the fastest and shortest time period using all available resources is quite important. To this end, a multi-echelon multi-objective forward and backward relief network is proposed that considers the location of hospitals, local warehouses, and hybrid centers which are hospital-warehouse centers in the pre-disaster phase. In the post-disaster phase, routing the relief commodities should be considered in the forward route. In the backward route, some vehicles that can transfer the injured people after delivering commodities, called hybrid transportation facilities, will take the injured to hospitals and hybrid centers. According to the degree of hardness, a hybrid Non-dominated Sorting Genetic Algorithm (NSGA-II) with Simulated Annealing (SA) and Variable Neighborhood Search (VNS) algorithms was proposed to solve the given problems. The results obtained from this hybrid algorithm were compared with those from NSGA-II and multi-objective SA-VNS using five metrics (i.e., the number of Pareto, mean ideal distance, spacing, diversity, and time), and it was concluded that the proposed hybrid algorithm outperformed the two foregoing algorithms.

1. Introduction

Natural disasters such as earthquake, flood, and storm annually inflict massive lethal and financial damages upon governments and societies. These disasters can potentially cause massive crises due to their large scope, considerable impacts on the material and human resources, and disruption of the natural life cycle, while pre-incident planning can considerably reduce the casualties resulting from these incidents. In case of disaster, the reduction in the potentials following the destruction of the infrastructure promotes the demand for logistic commodities and services [1]. In addition, proper and effective emergency responses require large-scale resources including human resources and commodities. In Search And Rescue (SAR), the emergency requirements comprise highly diverse and abundant resources and long periods. In the traditional

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design of emergency service facilities (including the firefighting facilities, emergency and first aid stations, and warehouses), it is extremely difficult to take actions because large-scale measures have to be taken as quickly as possible [2].

Disaster management as one of the major issues has long been a matter of controversy in most countries including Iran, and it is considered an important social and engineering concern around the globe. It generally refers to a set of rules and regulations on the prevention of or confrontation with the possible risks of any natural or human disaster. It predicts and plans a set of processes before, during, and following a disaster to prevent or minimize the financial and lethal damages. Every disaster management system follows a quadripartite cycle consisting of the following four phases:

1. **Prevention:** Calculations are performed to prevent the transformation of a hazard into a disaster or to mitigate its disastrous effects. This phase is one of the most important phases in the disaster management cycle;
2. **Preparedness:** In this phase, plans and solutions are predicted and designed to properly respond to earthquakes. Examples of these plans and solutions include positioning of distribution centers, stock of the relief commodities, and post-disaster communication modes;
3. **Response:** In this phase, rescue teams, relief commodities, and rescue equipment are dispatched and assigned to the affected areas immediately after the disaster;
4. **Rehabilitation:** The main objective her is to restore to the normal and improve the post-disaster situation. This phase is designed to meet the secondary and trivial needs of victims. It involves long-term measures taken to establish and reconstruct the society following the impact [3].

Given the significance of time and different forms of costs (i.e., financial costs and distances), researchers have attempted to optimize these parameters. The significance of time and cost (not solely financial costs) in the rescue and relief of the injured is doubled in case of disaster, especially during earthquakes and wars posing constant threats to human life. Moreover, undivided attention has been paid to this requirement in disaster management because equipment logistics can reduce many of the consequences of crises. Hence, the roles of routing and logistics in disaster management should be examined. As the most important and fundamental treatment institutions at times of disaster, rescue centers must be adequately prepared before an incident to be able to quickly and correctly respond to the subsequent crises. One of the most important strategies for improving the performance in disasters revolves around the delivery of the relief commodities to the victims and transfer of the injured properly and correctly to the rescue centers via the safest routes. Further, due to the uncertainty of demand for commodities in each region and transportation of the injured at times of disaster, it is substantially important to establish efficient relief methods for reducing the transportation risks and the costs.

To this end, the present study aims to propose a multi-echelon multi-product Mixed-Integer Programming (MIP) model for a forward and backward relief supply chain network that functions before and after a disaster. In the forward supply chain, emergency storage is in charge of providing materials to storage facilities or hospitals. In the backward one, injured people are returned to hospitals using transportation facilities. The main objective of this study is to design an efficient relief supply chain network to solve the location-allocation and routing problem considering the disruption risk. In addition, the ε-constraint method was employed to solve the model in small-scale problems. Furthermore, several meta-heuristic algorithms such as Non-dominated Sorting Genetic Algorithm (NSGA-II), MOVNS-SA, and a hybrid meta-heuristic algorithm made of the NSGA-II, Simulated Annealing (SA), and Variable Neighborhood Search (VNS) algorithms were utilized due to the model complexities. The proposed model offers the following advantages:

- Designing and modeling a multi-echelon relief supply chain for a disaster;
- Predicting hospitals, storage centers, or a combination of hospitals and storages;
- Proposing a method for locating the commodity distribution centers, transporting the relief commodities to the affected areas, transferring the injured from the affected areas, and locating the treatment centers for the subsequent medical services.

The rest of this paper is organized as follows. Section 2 presents literature review and research background. The problem statement and model formulation are given in Section 3. The proposed algorithms are discussed in Section 4. The computational results and those of sensitivity analysis are listed in Section 5. Finally, the concluding remarks and suggestions for further study are provided in Section 6.

2. Literature review

Disaster management and its subsets in designing emergency relief networks are among the most important concerns of operations researchers. Operations research modeling in disaster networks involves two phases: the pre-disaster preparedness and post-disaster response phases. Relief and disaster logistics operations are classified into two general categories:

1. Facility location;
2. Relief provision and transportation of commodities.

Based on this classification, facility location is approached from a geographical point of view with the consideration of some factors such as the cost and time of the responses in the context of relief logistics. This is a serious concern in the pre-disaster preparedness phase for the location of storages and storage of relief commodities in advance.

Modeling the location of relief facilities gains significance in the case of large-scale crises; therefore, the objective function and model details should be identified with utmost precision. Large-scale disasters are rare and infrequent; yet, they have massive lethal and financial consequences. One of the oldest studies on the emergency location problem was carried out by Toregas et al. [4] who solved a linear programming model for a coverage problem. Snyder [5] directly addressed the facility location-allocation problem about reliability and adopted a new approach to optimization of a supply chain under uncertain conditions for the first time. He was also the first researcher who directly studied the failure of facilities regarding the reliability of facilities in the facility location and allocation problem. Yi and Kumar [6] suggested the ant colony optimization algorithm for relief distribution. They divided the primary relief logistics problems into two consecutive decision-making phases, namely vehicle routing, and multi-commodity dispatching. Berkoune et al. [7] explored a multi-product, multi-storage, and multi-mode transportation SAR problem. They also introduced a mathematical model solved by a genetic algorithm that generated high-quality solutions and offered alternatives to disaster managers in a real-case disaster.

Emergency relief transportation was for the first time introduced in the 1980s by Knott [8] based on a routing model. A linear programming model was presented to determine the number of trips per camp to meet the demands and minimize the costs. Hamedi et al. [9] proposed a humanitarian supply chain transportation scheduling and routing model. A multi-objective routing algorithm was recommended for minimizing the travel time and reliability costs. The problem was then converted into a single-objective one by introducing a set of weights. The outputs of the routing algorithm were also routing and scheduling of the humanitarian truck fleet in the transportation network. In this algorithm, in case a part of the route was unreliable, that route was not selected due to the risk incorporated into the weighted objective function. Hence, it solved the problem through rescheduling. Liu et al. [10] proposed a framework for the post-disaster distribution of relief commodities. This framework consists of two modules:

(a) One for estimating the status and predicting the relief commodities demand and the delivery time;

(b) The other for relief distribution that determines the optimal distribution flows.

This model was supposed to minimize the total time of distribution of the relief commodities to satisfy the demands considering the uncertainty and decision-makers' risk.

Salmerón and Apte [11] developed a two-phase stochastic optimization model in which budget allocation was accurately employed to identify the optimal location of relief assets and decisions that needed to be taken accurately before an incident. Given that optimization aims at minimizing the expected casualties, this model consists of two phases. In the first phase, decisions show the distribution of the resources including the storages and medicinal facilities. In the second phase, decisions are about the logistics including the transportation facilities required for evacuation, delivery of the commodities required by the population, and transfer of the injured. Rawls and Turnquist [12] studied the relief requirements location problem to respond to natural disasters. They attempted to develop a relief response planning tool that determined the locations and quantities of different relief requirements to solve the location problem under uncertainty conditions. They proposed a two-phase stochastic MIP model as a powerful model considering the uncertainty in demand for the stored commodities and uncertainty in the post-incident availability of the transportation network. Mete and Zabinsky [13] suggested a stochastic optimization model to design the storage and distribution of medical items in the states of emergency under the uncertainty associated with demands and costs. The model primarily aims to determine the optimal location of the storages and the required stock before a disaster and reduce the risks posed to the storages that suffer seismic failures. Bozorgi-Amiri et al. [14] developed a multi-objective stochastic programming method for relief logistics under uncertainty. In this method, the demands, commodities, and costs of procurement and transportation are affected by this uncertainty. In addition, the uncertainty about the locations that may experience an increase in demand and possible post-incident destruction of some of the predicted commodities in the rescue centers as a result of the incident was taken into account. This model aimed to minimize the total sum of the expected costs as well as the variations of the total cost.

Barbarosoğlu and Arda [15] explored the operational and tactical scheduling of the helicopter activities in search and relief operations. They proposed a zero-level modeling framework centered on the transportation and routing problem during the first phase of the disaster.

Decisions on the helicopter fleet, pilot allocation, and final number of tours were offered by each helicopter to the affected areas in the affected zone. Özdamar et al. [16] examined a time-dependent dynamic transportation problem for the provision of multiple commodities by the supply centers to the distribution centers near the affected areas. They formulated a multi-period and multi-commodity network flow model to schedule the delivery and loading processes plus the amounts of loads delivered to these routes to gradually minimize the unmet demand. Their model was repeatedly solved in the given period to deliver relief commodities. The designed structure enables them to generate plans based on the variations in demand, supply, and size of the transportation fleet. Sheu [17] modeled a relief logistic network composed of suppliers, relief points, and affected areas. He introduced a decision support system consisting of three phases:

1. Demand prediction in the affected areas;
2. Classification of the affected areas by the estimated severity of the damage;
3. Prioritization of the affected areas for relief distribution.

Yi and Özdamar [18] described an integrated relief distribution model for logistical coordination and evacuation in the rescue and response operations. The logistic plan involves the dispatch of the commodities (including medicine and food) and SAR teams to the distribution centers in the affected areas as well as the evacuation and transfer of the injured to the emergency centers. Location of the medical personnel in the emergency centers was an integral part of their plan to protect the injured. Coutinho-Rodrigues et al. [19] introduced a multi-objective method based on the identification of the evacuation routes and shelters in an urban planning model in a location-allocation problem. This method puts the main focus on the identification of the number of relief facilities (shelters) and routes leading to the shelters.

Talarico et al. [20] solved the ambulance routing problem in a natural disaster emergency response scenario in which numerous wounded victims were in need of medical aid simultaneously. In their study, two mathematical models were defined to obtain the route plans and shorten the waiting time for the wounded people. A meta-heuristic local search method was employed in their study under uncertainty with the consideration of different parameters including the number of ambulances and hospitals, type of patients, and fleet capacity. Sharif and Salari [21] developed a comparative random search method to solve the transportation problem in SAR. In their study, the demand for a group of customers was met by several open routes using a limited number of vehicles in the central warehouse and the customer demands were met in each visit. The performance of the algorithm was also examined under different scenarios and its effectiveness was measured.

Gutjahr and Dzubur [22] proposed a two-objective and two-echelon optimization model to locate distribution centers in humanitarian logistical problems. They developed an exact algorithm to determine the Pareto boundary and combine the comparative ε-constraint method, branch-and-bound method, and Frank-Wolfe's algorithm. Rezaei-Malek et al. [23] introduced a two-objective model to design a relief logistic network, taking into account the importance of perishable commodities. The uncertain nature of the problem motivated the adoption of a powerful scenario-based stochastic approach. This model sought to simultaneously minimize the average response time and total operating expenses before the disaster as well as the post-incident penalty of the unmet demand and unused commodities.

Alem et al. [24] proposed a new two-stage stochastic network flow model to improve the decisions on rendering humanitarian aids to the victims of disasters. The practical features of this model include budget allocation, assessment of different fleets, logistics, and delivery times in a dynamic multi-stage horizon. Advanced risk-based methods (e.g., Conditional Value at Risk (CVaR)) were employed to improve the demand satisfaction policy. Cavdur et al. [25] designed a model for allocating the temporary emergency facilities to the transient or short-term SAR operations based on case studies of the earthquakes in Turkey. A two-stage stochastic programming approach was also proposed to solve the problem and minimize the total distance, unmet demand, and total number of facilities (considering the potential difficulties in accessing the facilities). In their method, facility and service allocations were carried out in the first and second phases, respectively. Five post-disaster scenarios were also formulated (e.g., traffic conditions and timings) and the likelihood of each scenario was taken into account. Jabbarzadeh et al. [26] proposed a combinatorial robust-stochastic optimization model and a Lagrangian relaxation method for designing a resilient supply chain that stands the supply and demand breaks and facility disruptions. Their technique also reduced the likelihood and impact of these disruptions through investment. In their model, the likelihood of disruption was considered to be an investment factor to spur investment and prevent any potential disruption under budget limitations. A disruption might result in complete shutdown of facilities or might reduce capacity. The performance of the proposed model was also analyzed using Monte-Carlo simulation.

Mohamadi and Yaghoubi [27] suggested a two-objective stochastic optimization model for the location of the points of transit and medical commodity distribution centers. In case of disaster, the prioritization of patients based on the severity of their injuries was one of the most important medical concerns. To meet the real-life conditions, the triage system and failure probability in the distribution centers and the routes of an urban region in Iran were addressed. The service level was eventually improved in the backup distribution centers. Sebatli et al. [28] developed a simulation-based approach to determine the demand for relief commodities before the entrance of the state agencies to the affected area. They designed a two-stage integer model for the allocation of temporary facilities and distribution of the relief commodities stored in these temporary facilities. Earthquake case studies were also carried out on 64 Turkish neighborhoods. Tavana et al. [29] designed a multiple humanitarian logistics network for the location of the central storages, pre-disaster management of the perishable commodities, and post-disaster routing. They employed the ε-constraint method and the NSGA-II to solve the model. Cao et al. [30] introduced a multi-objective mixed-integer linear programming model to design relief strategies and employed the genetic algorithm to solve their model. Torabi et al. [31] developed a two-stage and scenario-based fuzzy stochastic programming model to make arrangements between the relief commodity suppliers and humanitarian organizations. Their model considered the location of relief centers and logistic planning to reduce the costs.

Esfandiyari et al. [32] formulated a non-linear integer programming model for a fixed-charge location-allocation problem by hardening the network by providing backup facilities. The model was solved by a developed Lagrangian Decomposition Algorithm (LDA), and the obtained results were compared with CPLEX to guarantee that the LDA could perform more efficiently to deal with large-scale problems. Gharib et al. [33] designed a relief distribution network with three stages to deliver commodities to the affected areas. They clustered the affected areas into two parts: Cluster 1 referring to the usable land-routes after a disaster and Cluster 2 defines the route damage caused by the disaster and only air relief operation is possible. Then, an Adaptive Neuro-Fuzzy Inference System (ANFIS) was developed for pre-processing each cluster. Then, a heterogeneous multi-depot multi-mode vehicle routing problem was formulated to minimize the transportation time and maximize the reliability. To solve the problem, two meta-heuristic algorithms called NSGA-II and Multi-Objective Firefly Algorithm (MOFA) were proposed to obtain an optimal solution. Shavarani [34] proposed a multi-echelon facility location problem to determine the location of relief centers and refuel stations. In this model, the demand allocation is done based on the nearest neighborhood method. This problem was solved by a hybrid genetic algorithm and the results were examined through a case study. In their study, drones were considered for delivering relief commodities and recharge station locations were the tactical decision variables to increase the coverage radius of the drones.

A brief summary of the literature review is presented in Table 1 in which most studies have introduced a forward or backward model. However, in this study, a combination of the fleet system and service centers is designed specifically. Of note, the system reliability as the objective function is one of the contributions of the model. Seraji et al. [35] presented a two-stage mathematical model to improve post-earthquake conditions. In the first stage, the locations of shelters for the primary accommodation of people, location of first aid warehouses, and distances travelled by people from crisis areas to shelters were considered. The second stage investigated relief and coverage of demands after accommodating people in shelters. The mixed-integer linear programming model was solved using GAMS software and finally, the results were discussed.

Mohammadi et al. [36] developed a fuzzy scenario-based optimization model with the consideration of location of shelters, relief distribution centers, and telecommunication towers. A non-linear multi-objective model was formulated by considering failure in routes and relief distribution centers. Moreover, they considered integrated shelters with communication towers for better management and higher reliability. This model was solved using a heuristic method in conjunction with the Lp-metric method, and it was implemented on a flood case study in an urban district in Iran. Sotoudeh-Anvari et al. [37] suggested a stochastic multi-objective optimization model for trapped people in regions affected by disaster with uncertainty for the locations in which any survivor may be found. This model was solved through a stochastic dynamic programming approach. However, due to heavy computation, they converted the problem to a Multi-Criteria Decision Making (MCDM) problem and employed two efficient MCDM techniques for solving the problem, called TOPSIS and COPRAS techniques. As observed, there was excellent agreement between these methods in the search problem.

3. Model formulation

Based on the above discussion, the present paper is an attempt to guide the strategic decisions before

Table 1. Summary of the related literature review.

Row	Author	Year	Modelling method: Single objective	Modelling method: Multi objective	Planning time: Before disaster	Planning time: During disaster	Planning time: After disaster	Commodity type: Medical commodities	Commodity type: Non-medical commodities	Model specification: Time limit	Model specification: Routing	Model specification: Shortage	Model specification: Service level	Model specification: Justification	Model specification: Scenario-based	Model specification: Risk	Model specification: Perishability	Solution method: Exact method	Solution method: Heuristic or meta-heuristic
1	Rawls and Turnquist	2010			*		*	*	*			*			*				*
2	Mete and Zabinsky	2010		*	*			*			*	*			*	*		*	
3	Berkoune et al.	2012	*				*		*	*	*								*
4	Hamedi et al.	2012		*		*	*	*	*	*	*					*			*
5	Rodrigues et al.	2012		*				*		*	*					*			*
6	Bozorgi et al.	2013		*	*		*		*			*						*	
7	Talarico et al.	2014	*				*	*		*	*			*	*				*
8	Sharif & Salari	2015	*			*			*	*								*	*
9	Rezaei-Malek et al.	2016		*			*	*				*		*	*		*	*	
10	Alem et al.	2016	*		*	*		*	*		*		*		*	*			*
11	Cavdur et al.	2016		*			*		*				*		*			*	
12	Gutjahr et al.	2016		*			*		*			*						*	
13	Jabbarzadeh et al.	2016	*			*			*		*					*		*	*
14	Mohamadi & Yaghoubi	2017		*				*		*	*				*			*	
15	Sebatli et al.	2017	*		*	*		*	*		*								*
16	Gharib et al.	2017		*		*	*	*	*		*				*	*		*	*
17	Tavana et al.	2018		*	*		*	*		*	*	*					*	*	*
18	Shavarani et al.	2019	*				*	*	*		*								*
	This study			*	*		*	*	*		*	*	*	*		*		*	*

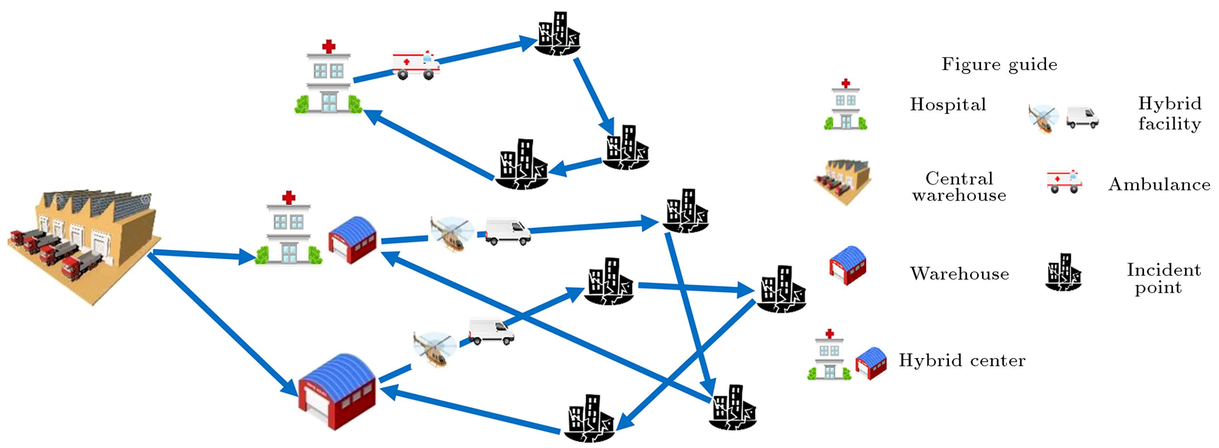

Figure 1. General schema of the logistics network.

and during the states of emergency by providing a mathematical model. As illustrated in Figure 1, an integrated forward and reverse supply chain network was designed in this study. In the forward route, the central warehouse provides local warehouses or hospitals with the required materials. In the backward route, the injured people are returned to the hospitals through the transportation facilities.

The locations of the affected areas and storages are fixed and predetermined. The proposed model predicts hybrid centers; in other words, storage, distribution, and treatment centers can be constructed in the same locations. The usage of facilities as hybrid centers is determined by the fixed costs of construction and variable costs of transportation. It can be stated that hybrid centers constitute a variable decision in this logistic network resulting in cost saving. In addition, a multi-product model was designed and solved to develop a more realistic situation and increase resiliency and generalizability. Since a quick response in disaster situations (e.g., earthquakes) is of significance, the maximal efficiency of any transportation facility should be obtained. One of the most important ways to serve logistics and relief proposes is aviation. Helicopters are good examples for sending commodities to the incident points and at the same time, they have the potential of transferring injured on the way back. Furthermore, given the significance of the golden time for survivors, some trucks on land shipment can be useful for injured collection during a disaster situation. Hence, two transportation systems are predicted: the first transportation system can simultaneously deliver the relief commodities to the affected areas and collect the injured people, which is called Hybrid Transportation Facilities (HTF); the second transportation system is only capable of collecting the injured people with different capacities, called an ambulance. Moreover, justice should be taken into account in the distribution of relief commodities among the demand points. Particularly, relief commodities must be distributed among the points of demand based on their priorities so that all demand points are equally treated according to their priorities and levels of emergency; otherwise, social chaos may erupt in addition to the existing disaster. Finally, the present study aims to obtain maximized reliability of the relief services and minimizes operating and fixed costs.

3.1. Assumptions

The following assumptions are considered in the proposed model:

- The model has three echelons;
- Warehouses are not allowed to transfer commodities with themselves;
- Each demand point can be supplied by one warehouse and it can send the injured to one hospital;
- Shortage is allowed;
- Transportation facilities are non-homogenous;
- One central warehouse for safety stock exists;
- All warehouses have a safety stock;
- Transportation facilities are divided into two parts: i) facilities that can only transfer injured people and ii) facilities that can dispense relief commodities and collect injured people on the way back (i.e., HTF).

In the following section, we define the mathematical factors used in the mathematical model.

3.2. Sets and indices

I	Sets of candidate locations for warehouse, hospital, or hybrid
J	Sets of incident points (demand points), indexed by j and $(u = 1, \cdots, J)$
K	Sets of relief commodities $(k = 1, \cdots, K, K+1)$, in which the last index $(K+1)$ refers to injured
V	Sets of HTFs $(v = 1, \cdots, V)$
W	Sets of ambulances, indexed by $(w = 1, \cdots, W)$
h	Index of central warehouse which is one central warehouse $h = 1$
l, i, j	Index of incident points and candidate locations for warehouse, hospital, or hybrid sets $(l, j, i = 1, \cdots, I + J)$

3.3. Parameters

Cap^{g}_{v}	Capacity of HTF type v for transferring relief commodities
Cap^{pe}_{v}	Capacity of HTF type v for transferring injured
Cap^{am}_{w}	Capacity of ambulance type w for transferring injured
F^{1}_{i}	Fixed cost of establishing a warehouse at location i
F^{2}_{i}	Fixed cost of establishing a hospital at location i
F^{3}_{i}	Fixed cost of establishing a hybrid center at location i
τ_{jk}	Shortage cost of relief commodity type k for incident point j
γ^{1}_{ik}	Capacity of the warehouse at location i for relief commodity type k
$\gamma^{2}_{i(K+1)}$	Capacity of the hospital at location i for the injured
γ^{3}_{ik}	Capacity of the hybrid center at location i for relief commodity type k and the injured
d_{jk}	Demand of incident point j for relief commodity type k
$d_{j(K+1)}$	Number of the injured at incident point j after incident
Bu	Maximum available budget for establishing facilities
Ψ	Maximum allowable shortage for relief commodities at each incident point
ω_k	Space used by relief commodity type k in HTFs

R_i^1 Risk of establishing warehouse at location i

R_i^2 Risk of establishing a hospital at location i

R_i^3 Risk of establishing a hybrid center at location i

R_{ijv} Risk of transferring relief commodities by HTF type v from a warehouse at location i to incident point j

C_{ljv}^1 Cost of transferring relief commodities from point l to point j by HTF type v

C_{ijw}^2 Cost of transferring the injured from point i to point j by ambulance type w

δ_{ju} Maximum justice level difference between each of two incident points j and $u(j \neq u)$

Inj_j 1 if incident point j has got injured; 0, otherwise

Ca_h Capacity of central warehouse h

SS_{ik} Quantity of relief commodity type k in the warehouse at location i

$Inst_{jv}$ Cost of transferring the injured at point j on the return way of HTF type v

rel_v Minimum expected reliability of selected route by HTF type v

3.4. Variables

y_{hik} Amount of relief commodity type k transferred from central warehouse h to warehouse at location i

x_{ijkv} Amount of relief commodity type k transferred from a warehouse at location i to incident point j

W_{ij}^1 1 if incident point j gets commodity from a warehouse at location i; 0, otherwise

W_{ij}^2 1 if injured from incident point j transferred to a hospital at location i; 0, otherwise

β_{jk} Shortage amount of commodity type k at incident point j

φ_j Weighted shortage at incident point j

M_i 1 if location i opens as a warehouse; 0, otherwise

N_i 1 if location i opens as a hospital; 0, otherwise

P_i 1 if location i opens as a hybrid center; 0, otherwise

Z_{ijv} 1 if HTF type v visits point j after point i; 0, otherwise

ZI_{ijw} 1 if ambulance type w visits point j after point i; 0, otherwise

LF_{jlkv} The amount of relief commodity type k transferred by HTF type v point j to point l

W_{ij}^3 1 if incident point j gets commodities from hybrid center i or transferred injured from point j to hybrid center i; 0, otherwise

ZR_{jv} 1 if the injured at point j is transported on the return way by the HTF v; 0, otherwise

3.5. Mathematical model

The proposed mathematical model and its details are demonstrated as follows:

$$\max \quad \mathrm{Re}=\prod_{i=1}^{I}(1-R_i^1)^{M_i}\cdot(1-R_i^2)^{N_i}\cdot(1-R_i^3)^{P_i}, \tag{1}$$

$$\begin{aligned}\min \quad C=&\sum_{i=1}^{I}(F_i^1 N_i+F_i^2 M_i+F_i^3 P_i)\\&+\sum_{j=1}^{J}\sum_{k=1}^{K}\tau_{jk}\beta_{jk}\\&+\sum_{j=1}^{I+J}\sum_{k=1}^{K}\sum_{l=1}^{I+J}\sum_{v=1}^{V}C_{ljv}^1 LF_{ljkv}\\&+\sum_{j=1}^{I+J}\sum_{i=1}^{I+J}\sum_{w=1}^{W}C_{ijw}^2 ZI_{ijw}\\&+\sum_{j=1}^{J}\sum_{v=1}^{V}Inst_{jv}ZR_{jv},\end{aligned} \tag{2}$$

s.t.:

$$\left(1-R_{ljv}\frac{LF_{ljkv}}{d_{jk}}\right)\geq rel_v$$
$$\forall\ l=1,\cdots,i+j,\quad j=1,\cdots,J,$$
$$v=1,\cdots,V,\quad K=1,\cdots,k, \tag{3}$$

$$\sum_{i=1}^{I+J}\sum_{v=1}^{V}Z_{ijv}=1 \qquad \forall\ j=1,\cdots,J, \tag{4}$$

$$\sum_{i=1}^{I}\sum_{j=1}^{J}Z_{ijv}\leq 1 \qquad \forall\ v=1,\cdots,V, \tag{5}$$

$$\sum_{j=1}^{J}Z_{ijv}\leq M_i+P_i$$
$$\forall\ i=1,\cdots,I,\quad v=1,\cdots,V, \tag{6}$$

$$\sum_{i=1}^{I+J} Z_{ijv} - \sum_{i=1}^{I+J} Z_{jiv} = 0$$

$$\forall\ j = 1, \cdots, J, \quad v = 1, \cdots, V, \tag{7}$$

$$\sum_{j=1}^{J} Z_{ijv} - \sum_{j=1}^{J} Z_{jiv} = 0$$

$$\forall\ i = 1, \cdots, I, \quad v = 1, \cdots, V, \tag{8}$$

$$\sum_{v=1}^{V} \sum_{j=1}^{J} x_{ijkv} \leq \left(\gamma_{ik}^{1} M_i + \gamma_{ik}^{3} P_i\right)$$

$$\forall\ i = 1, \cdots, I, \quad k = 1, \cdots, K, \tag{9}$$

$$-W_{ij}^{1} + \left(\sum_{u=1}^{J} Z_{iuv} + \sum_{u=1}^{J+I} Z_{ujv}\right) \leq 1$$

$$\forall\ i=1, \cdots, I, \quad j=1, \cdots, J, \quad v=1, \cdots, V, \tag{10}$$

$$\sum_{i=1}^{I} (W_{ij}^{1} + W_{ij}^{3}) = 1 \qquad \forall\ j = 1, \cdots, J, \tag{11}$$

$$x_{ijkv} \leq M.W_{ij}^{1} \qquad \forall\ i = 1, \cdots, I,$$

$$j = 1, \cdots, J, \quad k = 1, \cdots, K, \quad v = 1, \cdots, V, \tag{12}$$

$$\sum_{l=1}^{I+J} LF_{ljkv} - \sum_{l=1}^{I+J} LF_{jlkv} = \sum_{i=1}^{I} x_{ijkv}$$

$$\forall\ j=1, \cdots, J, \quad k=1, \cdots, K, \quad v=1, \cdots, V, \tag{13}$$

$$\sum_{j=1}^{J} \sum_{i=1}^{I+J} d_{j(K+1)} Z_{ijv} \sum_{u=1}^{I} W_{uj}^{3} \cdot Inj_j \leq Cap_v^{pe}$$

$$\forall\ z = 1, \cdots, V, \tag{14}$$

$$\sum_{i=1}^{I} \sum_{v=1}^{V} x_{ijkv} + \beta_{jk} = d_{jk}$$

$$\forall\ j = 1, \cdots, J, \quad k = 1, \cdots, K, \tag{15}$$

$$\sum_{i=1}^{I} F_i^1 M_i + F_i^2 N_i + F_i^3 P_i \leq Bu, \tag{16}$$

$$|\varphi_j - \varphi_u| \leq \delta_{ju} \qquad \forall\ j, u=1, \cdots, J, \quad u \neq j, \tag{17}$$

$$\varphi_j = \sum_{k=1}^{K} \tau_{jk} \beta_{jk} \qquad \forall\ j = 1, \cdots, J, \tag{18}$$

$$\sum_{k=1}^{K} \beta_{jk} \leq \Psi \sum_{k=1}^{K} d_{jk} \qquad \forall\ j = 1, \cdots, J, \tag{19}$$

$$\sum_{k=1}^{K} \omega_k LF_{ijkv} \leq Cap_v^{g} \qquad \forall\ i = 1, \cdots, I+J,$$

$$j = 1, \cdots, J, \quad v = 1, \cdots, V, \tag{20}$$

$$L_{ljkv} \leq M.Z_{ljv} \qquad \forall\ l = 1, \cdots, I+J,$$

$$j = 1, \cdots, J, \quad v = 1, \cdots, V, \quad k = 1, \cdots, K, \tag{21}$$

$$M_i + N_i + P_i \leq 1 \qquad \forall\ i = 1, \cdots, I, \tag{22}$$

$$W_{ij}^{2} + W_{ij}^{3} \leq N_i + P_i$$

$$\forall\ i = 1, \cdots, I, \quad j = 1, \cdots, J, \tag{23}$$

$$\sum_{i=1}^{I+J} \sum_{w=1}^{W} ZI_{ijw} = Inj_j^{*} \sum_{u=1}^{I} W_{uj}^{2}, \qquad \forall\ j = 1, \cdots, J, \tag{24}$$

$$\sum_{i=1}^{I} \sum_{j=1}^{J} ZI_{ijw} \leq 1 \qquad \forall\ w = 1, \cdots, W, \tag{25}$$

$$\sum_{j=1}^{J} ZI_{ijw} \leq N_i + P_i$$

$$\forall\ i = 1, \cdots, I, \quad w = 1, \cdots, W, \tag{26}$$

$$\sum_{l=1}^{I+J} ZI_{ijw} - \sum_{l=1}^{I+J} ZI_{jiw} = 0$$

$$\forall\ i = 1, \cdots, I, \quad w = 1, \cdots, W, \tag{27}$$

$$\sum_{j=1}^{J} ZI_{ijw} - \sum_{j=1}^{J} ZI_{jiw} = 0$$

$$\forall\ i = 1, \cdots, I, \quad w = 1, \cdots, W, \tag{28}$$

$$\sum_{j=1}^{J} \sum_{i=1}^{I+J} d_{j(K+1)}.ZI_{ijw} \leq Cap_w^{am} \quad \forall\ w=1, \cdots, W, \tag{29}$$

$$-W_{ij}^{2} + \left(\sum_{u=1}^{J} ZI_{iuw} + \sum_{u=1}^{J} ZI_{ujw}\right) \leq 1$$

$$\forall\ i=1, \cdots, I, \quad j=1, \cdots, J, \quad w=1, \cdots, W, \tag{30}$$

$$\sum_{j=1}^{J} d_{j(K+1)}.W_{ij}^2 \leq \left(\gamma_{i(K+1)}^2 N_i + \gamma_{i(K+1)}^3 P_i\right)$$

$$\forall\, i = 1, \cdots, I, \qquad (31)$$

$$\sum_{i=1}^{I} (W_{ij}^2 + W_{ij}^3) = Inj_j \qquad \forall\, j = 1, \cdots, J, \qquad (32)$$

$$\sum_{j=1}^{J} \sum_{v=1}^{V} x_{ijkv} \leq SS_{ik} \cdot (M_i + P_i) + \sum_{h=1}^{H} y_{hik}$$

$$\forall i = 1, \cdots, I, \quad k = 1, \cdots, K, \qquad (33)$$

$$\sum_{i=1}^{I} \sum_{k=1}^{K} \omega_k y_{hik} \leq Ca_h \qquad \forall\, h = 1, \qquad (34)$$

$$x_{ijk}, y_{hik}, q_{ik}, \beta_{jk}, \varphi_j, LF_{jlkv} \geq 0,$$

$$W_{ij}^1, W_{ij}^2, W_{ij}^3, M_i, N_i, P_i, Z_{ijv}, ZI_{ijw}, ZR_{jv} \in \{0, 1\}. \qquad (35)$$

Objective Function (1) shows the maximization of the system reliability. To determine the reliability of the entire relief centers in the proposed system, the reliability of every single center should be multiplied by one another. Objective Function (2) represents the second objective function as well as the minimization of the total cost of the relief logistic system. This phrase includes fixed costs of warehouses, hospitals and hybrid centers, shortage costs of relief commodities, transportation costs of commodities and injured people, and finally, loading costs at the incident points.

Constraint (3) ensures that the reliability of the selected routes for each vehicle should be greater than the minimal one expected by relief forces. Constraint (4) guarantees that every demand point is visited by one vehicle one time. Constraint (5) confirms that each vehicle can only get relief commodities from one warehouse. Constraint (6) states that when the warehouse at point $i$is selected for service, it can serve the demand points. Constraint (7) states that if a vehicle arrives at a demand point and serves it, it should exit that point. Constraint (8) ensures that if the vehicle is taken out of a warehouse point, it returns to that point at the end.

Constraint (9) is the capacity limit for warehouses and hospitals. According to Constraints (10)–(12), if demand points open in the service route of a warehouse, they should get service from that warehouse. Constraint (13) shows the number of commodities delivered to each demand point. Constraint (14) illustrates the capacity constraint of each vehicle for the injured. Constraint (15) shows the demand balance constraint for each incident point. Constraint (16) demonstrates the budget constraint. Constraint (17) depicts the level of justice in the distribution of relief items among demand points. According to this constraint, the difference between unsatisfied weighted demands between two incident points does not exceed the maximum amount set by the experts. In other words, this constraint and Constraint (11) trade-off the distribution of relief supplies between demand points fairly. In addition, there is a penalty for unsatisfied demands defined in Constraint (18) as a measure of justice. The maximum allowable amount of unsatisfied demands is also limited in Constraint (19).

Constraint (27) shows the capacity of vehicles for commodities. Constraint (21) allows the vehicles to give service to the points on their route. Constraints (22) and (23) explain the establishment permission for facilities at location i. In the case of opening the hospital or hybrid centers, they are allowed to take the injured people out of incident points. Moreover, if any of the injured at the incident points cannot be taken by HTFs, an ambulance must be sent to that point. This limit is illustrated in Constraint (24). Constraints (25)–(28) show the routing limits for ambulances, which are similar to Constraints (5)–(8), respectively. Furthermore, the capacity limit for ambulances is shown in Constraint (29). According to Constraint (30), the injured people at each demand point should be transferred to certain hospital. Moreover, the hospital capacity is demonstrated in Constraint (31). It is required to make sure that the injured people are collected by HTFs or ambulances as guaranteed in Constraint (32). Finally, in Constraints (33)–(34), the balancing of the commodities in the system and capacity limit for a central warehouse are demonstrated, respectively. Finally, Constraint (35) enforces the binary and non-negativity restrictions on the corresponding decision variables.

3.6. Linearization

In this section, the non-linear objective function and constraints as well as their transformations to the linear ones are discussed:

- Due to the nonlinearity of Objective Function (1), the following approximation is used to linearize the first objective function:

$$\max \quad \mathrm{Re} = \ln \prod_{i=1}^{I} (1 - R_i^1)^{M_i} \cdot (1 - R_i^2)^{N_i} \cdot (1 - R_i^3)^{P_i}. \qquad (36)$$

  Therefore, the above objective function can be written as follows:

$$\max \quad \ln \mathrm{Re} = M_i \cdot \ln(1 - R_i^1) + N_i \cdot \ln(1 - R_i^2) + P_i \cdot \ln(1 - R_i^3). \qquad (37)$$

  Consequently, if $\ln \mathrm{Re}$ is maximal, Re will be maximized. Therefore, Objective Function (1) is replaced by:

$$\max \quad \mathrm{Re} \cong \max \ln \mathrm{Re} = M_i \cdot \ln(1-R_i^1) + N_i \cdot \ln(1-R_i^2) + P_i . \ln(1-R_i^3). \quad (38)$$

- Constraint (14), which is the product of two binary decision variables, is nonlinear. To transform it to its linear counterpart, Constraint (14) is replaced by the following constraints:

$$\sum_{j=1}^{J} d_{j(K+1)} ZR_{jv} \leq Cap_v^{pe} \qquad \forall\, v=1,\cdots,V, \quad (39)$$

$$\left(\sum_{i=1}^{I+J} Z_{ijv} + \sum_{u=1}^{I} W_{uj}^2\right) Inj_j \leq 1 + ZR_{jv}, \quad (40)$$

$$ZR_{jv} \leq Inj_j \cdot \sum_{i=1}^{I+J} Z_{ijv}, \quad (41)$$

$$ZR_{jv} \leq Inj_j \cdot \sum_{u=1}^{I} W_{uj}^3. \quad (42)$$

Constraint (39) indicates the capacity of the vehicle to return the injured to the hybrid facilities. Constraint (40) ensures that if the injured at the demand point j are to be served by a hybrid center and the vehicle v visits that demand point, the variable $ZR_{jv} = 1$ and that point must be considered in the vehicle capacity. Constraint (41) illustrates that if the demand point j is not visited by the vehicle v, $ZR_{jv} = 0$ and the demand for that point is not considered in the vehicle capacity. Finally, Constraint (42) guarantees that if the injured at point j do not receive service from the hybrid centers, $ZR_{jv} = 0$ and the demand for that point is not considered in the capacity of vehicle v.

4. Proposed algorithms

To solve the model, a hybrid meta-heuristic algorithm consisting of the NSGA-II, SA and VNS algorithms is proposed. The solutions are also fully described below.

4.1. NSGA-II

The NSGA-II is one of the most efficient and well-known multi-objective optimization algorithms, which was developed by Deb et al. [38]. This algorithm creates less operational complexity than other algorithms. In this algorithm, a population of children was first generated by the parent population, and the size of each population equals N. These two populations are merged to create a population with $2N$ members. This population is also classified based on non-dominated sorting, and the new *N-member* population consisting of the best members is identified. Each population class is called a front.

4.2. SA

SA algorithm is a local search algorithm that is capable of avoiding local optima. This algorithm enjoys several advantages such as high convergence rate, ease of use, and measures designed, to name a few, to avoid the local optima that have attracted researchers. The SA algorithm revolves around the annealing of metals. It was first introduced by Metropolis et al. [39] and then, it was implemented by Kirkpatrick [40] to solve the combinatorial optimization problems. The similarities between the combinatorial optimization problems and a physical object originate from the following features:

- The possible solutions to the combinatorial optimization problem correspond to the object states;
- The value of the objective function for a possible solution corresponds to the energy of the object. Moreover, when we heat an object, it gradually expands and its energy rises due to the expansion and heat. In this case, the atoms sound chaotic but when the object is cooled down gradually, the arrangement of the atoms becomes less chaotic and the system is considered to be functioning on a low energy level. The SA algorithm, often called gradual freezing process, is inspired by the aforesaid physical freezing phenomenon.

4.3. VNS

Mladenovic [41] introduced VNS algorithm, widely used for solving optimization problems. Hansen and Mladenović [42] introduced the VNS algorithm for the optimization of the p-median problem. Brimberg et al. [43] employed this algorithm to solve the multi-source Weber problem, and Ribeiro and Souza [44] took the advantage of this algorithm to optimize the spanning tree problem that is a sub-graph of a graph. The VNS algorithm generally begins with the initial solution $x \in S$ where S is the problem space solution. Two primary search engines, namely the shake and local search processes, were also employed to search the solution space. While the former was used as a refresher to refresh the local search loop, the latter carried out the primary extensive search. The shaking process also increased the solution diversity by switching from a neighborhood structure to another neighborhood structure [45]. The functionality of the VNS algorithm was contingent upon the efficiency of the neighborhood structures, which should be selected with utmost precision. This method is called the VNS algorithm due to the variations of the neighborhood structure in the course of the search process.

4.4. Proposed hybrid algorithm

In this study, a new hybrid algorithm was developed with the combination of NSGA-II, Multi Objective Simulated Annealing (MOSA), and Multi Objective Variable Neighborhood Search (MOVNS). The main structure of the proposed algorithm is based on NSGA-II; however, solutions produced by crossover

1) Set the algorithm's parameters ($Max\ it, Te, Kmax$)
2) For each $i = 1, \ldots, M$, where M is the population size
   a) Generate $P[i]$ randomly
   b) Evaluate the objective function of $P[i]$
3) $t = 0$ (number of iterations)
4) Transfer non-dominated solution of P in A , where A is an external archive
   a) Assign the rank based on Pareto dominance and calculate the crowding distance of individuals in each front
   b) Sort the solution based on the crowding distance and rank
5) Repeat
   a) Select a parent
   b) Apply crossover
   c) Apply mutation
   d) Check feasibility of $Pnew[i]$ solution and do possible repairing
   e) Evaluate the objective function
6) Set k=1 for each offspring until K_{max}
   a) Apply shaking $P'[i] \leftarrow Pnew[i]$
   b) Apply local search method(k) , $P''[i] \leftarrow P'[i]$
   c) if $P''[i]$ dominated $P[i]$, then K=1 and $Pnew[i] \leftarrow P''[i]$
   d) else if $random(0,1) < \min_k exp^{\frac{-\Delta f}{T}}$ then $k = 1$; else, $t = t + 1$
7) Add new offspring ($Pnew$) to parent population (P)
8) Transfer non-dominated solution of P in A .(A is external archive)
9) Assign rank based on Pareto dominance and calculate crowding distance of individual in each front
10) Sort the solution based on the crowding distance and rank
11) Apply the elitism selection technique and select parent population for the next generation
12) $t = t + 1$

Figure 2. The proposed pseudo code.

and mutation functions are improved by a neighborhood approach. The neighborhood approach is the combination of two neighborhood search algorithms, i.e., MOSA and MOVNS. The annealing and freezing notions are incorporated into the SA algorithm to improve the neighborhood generation efficiency in the VNS algorithm. In the neighborhood approach of the proposed algorithm, a new solution is created in the vicinity of the previous one. In case the new solution improves the objective function, the new solution is remained; otherwise, the new solution is rejected, which may result in permanent entrapment in the local optimal. However, in SA, the local optimal solutions are completely avoided by escaping the local optima region. The algorithm leaves the local optima region through the possible approval of the bad solutions. The pseudo code of the hybrid proposed algorithm is illustrated in Figure 2.

With the consideration of a combination of SA and VNS in the proposed algorithm, the neighborhood process is completed for each child generated by the mutation and crossover operators. It eventually improves the diversity of the solution, thereby avoiding the local optimal.

4.5. Parameter tuning and specifications of test problems

In the following, the Taguchi design method is used to perform the parameter tuning for the proposed algorithms. Test results generally serve to estimate or analyze the importance of the given factors based on measurable solutions. In this method, the difference in the test data or the variances of the solution variables was taken into account. Furthermore, the signal-to-noise ($\frac{S}{N}$) ratio is often used to facilitate this analysis. The simplest form of the $\frac{S}{N}$ ratio is the ratio of the mean signal to noise standard deviation, which is the inverse form of the coefficient of variation of the system response. For each parameter, the surface with a larger $\frac{S}{N}$ value is deemed to have the optimal and acceptable value. Moreover, the Number Of Pareto (NOP) solutions was utilized as the measure of the solution. Four metrics including the number of initial population size ($npop$), maximum number of iterations (*max-it*), mutation coefficient, and crossover coefficient are considered in the NSGA-II for parameter tuning, the results of which are shown in Table 2.

Three factors including the maximum number of iterations, temperature decrease rate, and initial temperature were employed in VNS-SA. The initial temperature equals the objective function resulting from the first iteration for all the objective functions. Table 3 lists the values of the first two parameters.

Six factors called the initial population size, maximum number of iterations (max-it), mutation rate, crossover rate, temperature decreasing rate (mutation), and initial temperature (crossover) were taken into account in the NSGA-II. The initial temperature equals the objective function resulting from the first iteration for both objective functions. Figure 3 presents the S/N results of the proposed algorithm. Table 4 presents the optimal parameter values.

Given the novelty of the proposed model and investigation results, there is no standard sample of the research problem. In this respect, the randomly generated sample problems were used and solved. In this study, 30 problems were solved to generate solutions, as shown in Table 5. The size of these problems varies from small to large sizes depending on the problems given in the research literature, as shown in Table 5. Moreover, 5 to 100 regions and 2 to 30 potential depots were selected. The first, second, and last 10 problems are small-, medium-, and large-sized ones, respectively. In addition, the problem parameters were randomly generated to assess the performance of the proposed algorithms, and a uniform distribution function was employed to generate the numbers. The parameters of the proposed algorithms were then generated in the following range based on the related papers. The range of the parameters used in the test problems is depicted in Table 6. The budget (Bu) is also considered equal to 0.75 of the cost to explain the problem in different samples. Finally, the allowable shortage (Ψ) is 0.3 of the demand at each point of demand.

Table 2. Non-dominated Sorting Genetic Algorithm (NSGA-II) parameter tuning results.

Mutation rate	Crossover rate	Initial population	Iteration number
0.3	0.7	50	200

Table 3. VNS-SA algorithm parameter tuning results.

Cooling rate	Iteration number
0.97	800

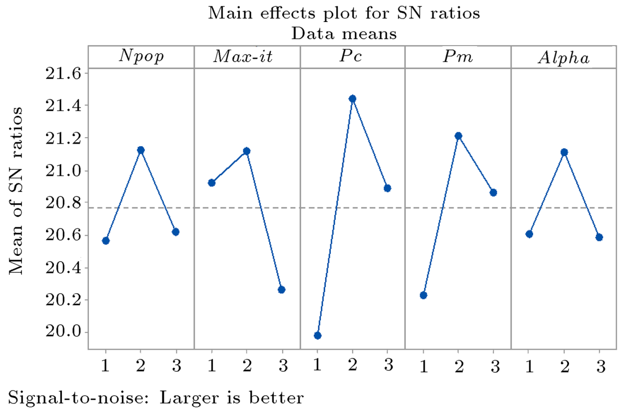

Figure 3. S/N ratio plot for each level of the factors for the proposed algorithm.

4.6. Solution representation

The chromosome consists of four parts and each part is a matrix. The first matrix determines the type of the centers reopened: "1" represents a center reopened as a depot; "2" stands for a center reopened as a hospital; "3" is a center reopened as a hybrid center; and "0" represents a center that has not been reopened. The second matrix shows the vehicles allocated to the centers reopened. The number of the cells in this matrix equals that of vehicles, and the numbers in each cell show the number of the center allocated. The third matrix shows the victims assigned to each vehicle. This matrix has two rows and the number of its columns equals that of the demand points. The first row shows the data on the shipment of the relief commodities, while the second row shows the data on the transfer of the injured. The fourth matrix also presents the amount of commodities sent from each node to each point of demand. Figure 4 illustrates the demonstration of the problem solution.

Figure 4 presents a demonstration of the solution to a sample problem with six potential centers, seven points of demand, three products, and six vehicles. As seen in Section 1, Center 1 is reopened as a depot and Center 5 is a hospital. Centers 1 and 6 are multi-purpose centers and Centers 4 and 2 are not reopened. In the second part of this chromosome, the vehicles are allocated to different centers. For instance, Vehicles 2 and 3 are assigned to Center 1. In Section 3, different points of demand are allocated to the vehicles. The first row identifies each vehicle that delivers the relief commodities to the victims. The second row shows

Table 4. Parameter tuning results for the proposed algorithm.

Cooling rate	Mutation rate	Crossover rate	Initial population	Iteration number
0.95	0.2	0.8	40	125

Table 5. Size of test problems.

No.	Warehouse points	Demand points	Emergency commodities	Transportation facilities	Ambulance
1	2	5	2	3	2
2	3	6	3	3	3
3	3	7	3	3	3
4	4	7	4	3	5
5	4	8	4	4	7
6	5	9	5	4	8
7	6	10	6	4	9
8	6	12	6	5	10
9	7	12	7	5	12
10	8	15	8	5	12
11	9	15	9	5	12
12	10	18	10	5	15
13	10	20	10	6	15
14	12	22	12	6	18
15	12	25	12	6	20
16	15	28	15	7	25
17	15	30	15	8	25
18	18	35	15	10	30
19	18	40	18	12	30
20	20	45	18	15	30
21	20	50	18	15	35
22	22	55	20	18	35
23	22	60	20	18	35
24	25	65	22	18	40
25	25	70	22	20	40
26	28	75	25	20	45
27	28	80	25	25	45
28	28	85	30	25	45
29	30	90	30	30	50
30	30	100	30	30	50

Table 6. Range of random data of the parameters used in the test problems.

Parameters	Scale	Parameters	Scale
Cap_v^g	Uniform (250, 450)	C_{ijw}^2	Uniform (40, 100)
Cap_v^{Pe}	Uniform (10, 15)	Ca_h	Uniform (1000, 1500)
Cap_w^{am}	Uniform (15, 30)	SS_{ik}	Uniform (J^*120, J^*150)
F_i^1	Uniform (20, 30)$^*10^5$	ω_k	Uniform (0.8, 1.20)
F_i^2	Uniform (50, 60)$^*10^5$	R_i^1	Uniform (0.01, 0.10)
F_i^3	Uniform (60, 80)$^*10^5$	R_i^2	Uniform (0.01, 0.10)
τ_{jk}	Uniform (200, 350)	R_i^3	Uniform (0.01, 0.10)
γ_{ik}^1	Uniform (0.25^*J^*80, 0.5^*J^*80)	R_{ijv}	Uniform (0.05, 0.30)
γ_{ik}^3	Uniform (0.2^*J^*70, 0.5^*J^*70)	C_{ljv}^1	Uniform (20, 80)
$\gamma_{i(K+1)}^2$	Uniform (0.2^*J^*10, 0.5^*J^*10)	δ_{pq}	Uniform (30, 50)
d_{jk}	Uniform (50, 100)	rel_v	Uniform (0.7, 0.80)
$d_{j(K+1)}$	Uniform (3, 6)	$\gamma_{i(K+1)}^3$	Uniform (0.2^*J^*8, 0.5^*J^*8)

Center 1	Center 2	Center 3	Center 4	Center 5	Center 6
3	0	1	0	2	3

Matrix 1

Vehicle 1	Vehicle 2	Vehicle 3	Vehicle 4	Vehicle 5	Vehicle 6
Center 6	Center 1	Center 1	Center 6	Center 3	Center 5

Matrix 2

Demand 1	Demand 2	Demand 3	Demand 4	Demand 5	Demand 6	Demand 7
Vehicle 1	Vehicle 4	Vehicle 3	Vehicle 2	Vehicle 3	Vehicle 4	Vehicle 5
Vehicle 6	Vehicle 4	Vehicle 3	Vehicle 2	Vehicle 3	Vehicle 6	Vehicle 6

Matrix 3

	Commodities type 1	Commodities type 2	Commodities type 3
Demand 1	100	50	150
Demand 2	150	80	200
Demand 3	120	60	250
Demand 4	140	50	100
Demand 5	180	100	150
Demand 6	200	40	50
Demand 7	100	30	150

Matrix 4

Figure 4. Illustration of solution representation.

$Paret_1(1:Alpha)$				$Paret_2(1+Alpha:N)$			First child				
2	1	0		2	3	$\longrightarrow$	2	1	0	2	3
$Paret_2(1:Alpha)$				$Paret_1(1+Alpha:N)$			Second child				
0	2	3		1	0	$\longrightarrow$	0	2	3	1	0

Figure 5. Illustration of the crossover operator strategy for parts 1 to 3 of the chromosome.

the vehicles carrying the victims. The injured are transferred to the hospitals by ambulance and, then, to multi-purpose centers by vehicles. The fourth part also presents the relief commodities sent to the victims.

4.7. Generating the initial population

First, a random sequence of the potential centers is generated:

a) A number between 0 and 3 is randomly assigned to each center and the type of the centers reopened is identified;

b) In this phase, the vehicles are allocated to the centers based on the type of the centers reopened;

c) The quantity of relief commodities allocated to each victim is randomly determined per commodity;

d) In this step, the victims are allocated to the vehicles based on the demand met in Step C, the vehicles allocated to the centers in Step B, and the capacity limitations;

e) The optimal path for each vehicle is identified through the algorithm proposed by Clarke and Wright [46];

f) Finally, the objective functions are calculated.

4.8. Crossover and mutation operators

In this study, the single-point operator serves as a crossover operator in parts 1–3. This operator is expressed by:

$$ch_1 = [Paret_1(1\colon Alpha), Paret_2(1 + Alpha\colon N)], \quad (43)$$

$$ch_2 = [Paret_2(1\colon Alpha), Paret_1(1 + Alpha\colon N)], \quad (44)$$

where $Paret_1$ and $Paret_2$ denote the selected parents, respectively. In addition, $Alpha$ is a cut-off point between 1 and the matrix length, and ch_1 and ch_2 are the children. For instance, the schematic of this operation for the first part of the chromosome is presented in Figure 5 ($Alpha = 3$).

A round operator is also used for part 4, as expressed in the following:

$$ch_1 = round(Paret_1{}^{*}Alpha + Paret_2{}^{*}(1 - Alpha)), \quad (45)$$

$$ch_2 = round(Paret_2{}^{*}Alpha + Paret_1{}^{*}(1 - Alpha)), \quad (46)$$

where $Paret_1$ and $Paret_2$ are the selected parents, respectively. Alpha varies between 0 and 1 and has the same dimension as the chromosome matrix. Further, ch_1 and ch_2 are the resulting children. Finally, both solutions are rounded to obtain integers. The schematic of this operation is also depicted in an example in Figure 6 ($Alpha = 0.4$).

In this study, for the mutation operator, the swap operator is used for the first three parts of the chromosome and the insertion operator is used for the fourth part of the chromosome. To this end, one cell is selected from the fourth part of the chromosome and the amount of its commodity changes. The stopping condition in this algorithm is to set the maximum

$Paret_1 * Alpha$				$Paret_2 * (1 - Alpha)$				First child		
20	80	30	+	50	50	60		38	62	48
50	30	60		30	40	20	→	38	36	36
40	50	40		20	30	50		28	38	46
$Paret_1 * (1 - Alpha)$				$Paret_2 * Alpha$				Second child		
20	80	30		50	50	60		32	68	42
50	30	60	+	30	40	20	→	42	34	44
40	50	40		20	30	50		32	42	44

Figure 6. Illustration of the crossover operator strategy for part 4 of the chromosome.

1	4	3	0	2	5	8	0	0	7	6
1	8	3	0	2	5	4	0	0	7	6

Figure 7. SWAP operator.

1	4	3	0	2	5	8	0	0	7	6
1	4	5	2	0	3	8	0	0	7	6

Figure 8. Inversion operator.

1	4	3	0	2	5	8	0	0	7	6
8	4	3	0	2	5	1	0	0	7	6

Figure 9. Insertion operator.

number of iterations. Moreover, tournament selection method is used for selecting parents from the old population.

4.9. Methods for neighborhood generation

In this study, three neighborhood generation operators are used for each of the four solution demonstration matrices. In other words, a total of 12 neighborhood generation methods are used to generate the neighborhoods:

a) **SWAP operator:** For this operator, two cells are selected and the values of the two cells are swapped. The performance of the SWAP operator is depicted in Figure 7;

b) **Inversion operator:** For this operator, two cells are selected, and the values between the two cells are swapped. The performance of the inversion operator is depicted in Figure 8;

c) **Insertion operator:** One cell is selected from each matrix and the number in the selected cell varies. The performance of the insertion operator is depicted in Figure 9.

4.10. Performance metrics

There are two groups of metrics (convergence and dispersion) used for assessing the multi-objective meta-heuristic algorithms. In this study, six metrics made of these two groups were used for comparison purposes.

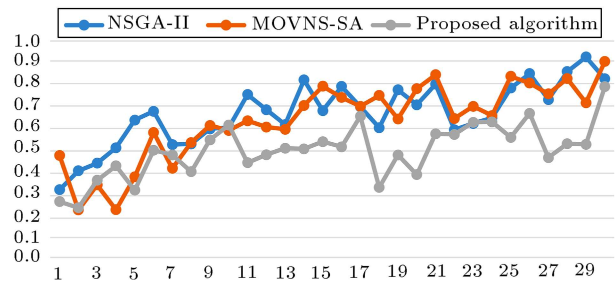

Figure 10. Summary of the performance of the proposed algorithm in terms of the MID metric.

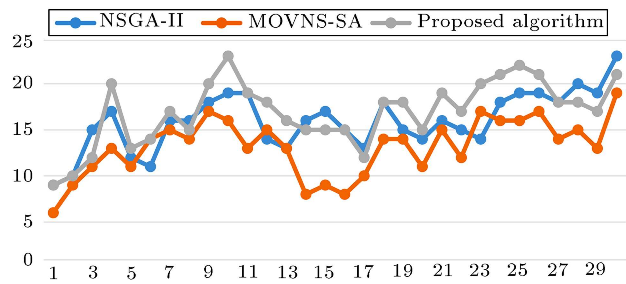

Figure 11. Summary of the performance of the proposed algorithm in terms of the Number Of Pareto (NOP).

The first group of metrics includes the NOP solutions, Mean Ideal Distance (MID), and set cover metrics. The second group of metrics comprises the spacing metric, diversity metric, and maximum expansion metric. Finally, the algorithm running time metric is used to compare the calculation requirements [47–50].

5. Computational results

In this paper, 30 randomly generated problems were solved. The details of the problems were provided in the previous section. Prior to explaining the metric results of each algorithm, it should be mentioned that a higher value for NOP solutions and diversity values are deemed more optimal. Concerning the MID and spacing metrics, smaller values are considered to be more optimal. Shorter problem-solving times are also considered more optimal. Tables 7 and 8 show the value for each of these metrics are listed.

Figures 10 to 14 show the graphical presentations

Table 7. Computational results for the Mean Ideal Distance (MID), Number Of Pareto (NOP), and time metrics.

Test problem	NSGA-II			MOVNS-SA			Proposed algorithm		
	MID	NOP	Time	MID	NOP	Time	MID	NOP	Time
1	0.327	9	11.95	0.480	6	9.92	0.274	9	13.56
2	0.411	10	21.75	0.237	9	14.81	0.247	10	26.47
3	0.445	15	26.99	0.348	11	23.16	0.369	12	34.59
4	0.514	17	30.88	0.238	13	29.34	0.433	20	43.33
5	0.637	12	38.22	0.384	11	35.98	0.325	13	57.81
6	0.676	11	39.27	0.582	14	37.48	0.503	14	67.21
7	0.528	16	48.35	0.422	15	45.76	0.482	17	78.34
8	0.531	16	67.42	0.537	14	50.84	0.407	15	88.60
9	0.598	18	85.81	0.613	17	78.55	0.549	20	101.40
10	0.604	19	105.11	0.591	16	81.83	0.615	23	121.51
11	0.751	19	147.97	0.634	13	102.46	0.447	19	162.26
12	0.683	14	170.60	0.606	15	125.80	0.483	18	198.95
13	0.617	13	195.69	0.596	13	143.10	0.512	16	222.16
14	0.816	16	222.72	0.702	8	153.82	0.509	15	254.16
15	0.679	17	281.88	0.788	9	198.76	0.541	15	307.61
16	0.787	15	323.78	0.738	8	216.34	0.518	15	351.07
17	0.696	13	384.42	0.698	10	281.41	0.654	12	419.47
18	0.603	18	470.83	0.747	14	340.37	0.337	18	494.28
19	0.772	15	533.28	0.642	14	402.26	0.482	18	561.33
20	0.705	14	584.63	0.777	11	492.02	0.394	15	656.76
21	0.797	16	717.16	0.839	15	591.30	0.576	19	837.41
22	0.594	15	883.55	0.644	12	668.06	0.573	17	980.89
23	0.622	14	1068.87	0.698	17	887.63	0.627	20	1273.90
24	0.647	18	1232.54	0.657	16	1,028.78	0.629	21	1502.02
25	0.780	19	1423.22	0.832	16	1,269.50	0.560	22	1861.78
26	0.844	19	1602.05	0.802	17	1,413.74	0.667	21	2122.54
27	0.728	18	1844.75	0.754	14	1,634.82	0.470	18	2489.46
28	0.853	20	2238.28	0.822	15	1,776.97	0.532	18	2,890.76
29	0.918	19	2528.71	0.714	13	2,191.20	0.529	17	3,267.94
30	0.821	23	3022.91	0.898	19	2,650.21	0.786	21	3,787.53

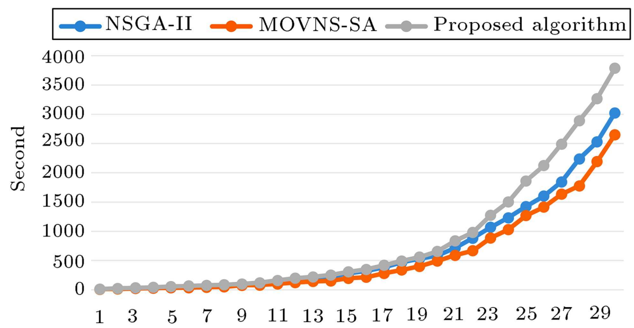

Figure 12. Summary of the performance of the proposed algorithm in terms of time metric.

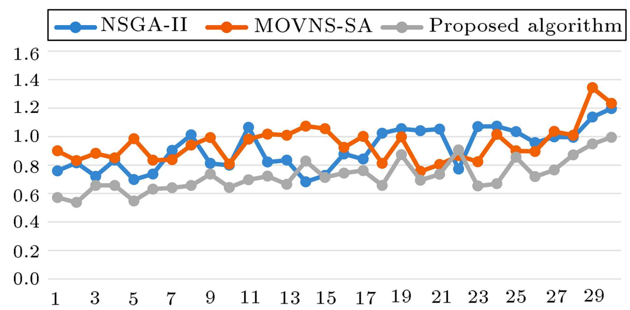

Figure 13. Summary of the performance of the proposed algorithm in terms of spacing metric.

of the results of 30 numerical problems solved by the five aforesaid metrics. While the horizontal axis shows the problem number, the vertical axis shows the metric value. The first diagram illustrates the performance of the two algorithms for the MID metric. As observed, the proposed algorithm outperforms the other algorithms, thus yielding more optimal results than the other two algorithms. The NOP solutions is also given in Figure 11, where the proposed algo-

Table 8. Computational results for the spacing and diversity metrics.

Test problems	NSGA-II		MOVNS-SA		Proposed algorithm	
	Spacing	Diversity	Spacing	Diversity	Spacing	Diversity
1	0.760	1.006	0.900	1.016	0.572	1.062
2	0.816	1.073	0.832	0.931	0.538	1.025
3	0.721	0.909	0.882	0.994	0.657	1.020
4	0.835	0.810	0.850	1.069	0.657	1.146
5	0.698	0.986	0.986	1.050	0.548	1.115
6	0.737	1.048	0.834	0.789	0.631	1.090
7	0.904	0.761	0.838	0.691	0.640	0.938
8	1.012	0.837	0.940	0.890	0.656	0.956
9	0.812	0.865	0.994	0.801	0.736	1.135
10	0.799	0.682	0.808	0.817	0.643	1.017
11	1.066	0.683	0.982	0.788	0.696	0.975
12	0.821	0.863	1.018	0.830	0.722	0.959
13	0.834	0.687	1.010	0.737	0.665	0.896
14	0.683	0.819	1.074	0.895	0.828	0.983
15	0.727	0.789	1.056	0.791	0.713	0.869
16	0.878	0.806	0.924	0.761	0.744	0.943
17	0.842	0.777	1.002	0.653	0.761	1.027
18	1.024	0.651	0.812	0.771	0.657	0.923
19	1.055	0.766	0.998	0.635	0.873	0.972
20	1.042	0.783	0.756	0.740	0.694	0.877
21	1.053	0.605	0.804	0.625	0.735	0.779
22	0.772	0.870	0.866	0.631	0.907	0.740
23	1.071	0.708	0.824	0.785	0.653	0.765
24	1.073	0.791	1.016	0.535	0.669	0.841
25	1.035	0.723	0.900	0.680	0.856	0.856
26	0.958	0.580	0.896	0.595	0.719	0.823
27	0.998	0.662	1.036	0.552	0.765	0.791
28	0.995	0.630	1.010	0.423	0.872	0.671
29	1.137	0.491	1.344	0.448	0.948	0.540
30	1.197	0.412	1.234	0.367	0.995	0.510

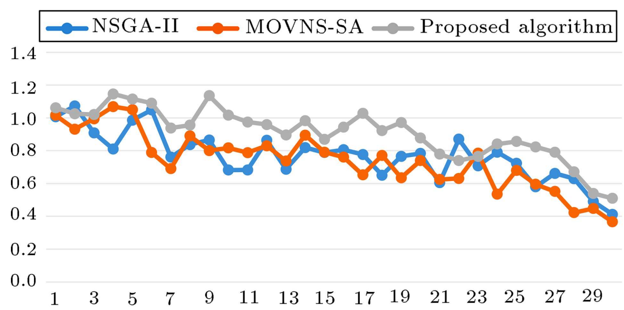

Figure 14. Summary of the performance of the proposed algorithm in terms of diversity metric.

rithm generates more Pareto solutions for most sizes. Figure 12 depicts the calculation time. According to this figure, the calculation time required by the proposed algorithm is longer due to the simultaneous use of the operators of mutation, composition, and neighborhood generation. Figure 13 presents the MID metric results of the two algorithms. In this figure, the spacing of Pareto solutions yielded by the proposed algorithm is longer and this algorithm results in more regular solutions. The diversity metric is also given in Figure 14. As observed, in most sample problems, the proposed algorithm produced more diverse solutions due to the diversity of the used operators.

The algorithms should be compared by statistical analyses to obtain a more effective analysis. Therefore, the mean equivalence test and Tukey's statistical hypothesis test were carried out to examine the performance of the algorithms more precisely and finally assess the performance of the algorithms against different metrics. Here, the hypothesis test on the equivalence of the means of three mutual populations is carried out. In this test, the null hypothesis is about the equivalence of the means of metrics in three

Table 9. Statistical hypothesis results for the algorithms.

Metrics	F test	NSGA-II			MOVNS-SA			Proposed algorithm		
	p-value	Mean	95% CI	Grouping	Mean	95% CI	Grouping	Mean	95% CI	Grouping
Spacing	0.000	0.9118	(0.8646, 0.9591)	A	0.9475	(0.9003, 0.9948)	A	0.7250	(0.6778, 0.7722)	B
Diversity	0.000	0.7689	(0.7096, 0.8283)	B	0.7430	(0.6837, 0.8024)	B	0.9081	(0.8487, 0.9674)	A
MID	0.000	0.666	(0.6134, 0.7189)	A	0.634	(0.5813, 0.6868)	A	0.501	(0.4482, 0.5537)	B
NOP	0.000	15.933	(14.747, 17.120)	A	13.167	(11.980, 14.353)	B	16.933	(15.747, 18.120)	A
Time	0.481	678	(356, 1001)	A	566	(244, 888)	A	1073	(520, 1165)	A

algorithms at a significance level of 95%. In case the resulting p-value is smaller than 0.05 (i.e., 1–0.95), the null hypothesis is rejected and the significant difference between the performance assessment metrics of the three algorithms is confirmed, and vice versa. The results of testing the three-population hypothesis using 5 metrics are presented in Table 9. The p-value for the spacing, diversity, MID, and NOP solution metrics is smaller than 0.05, hence the rejection of the null hypothesis. However, the p-value equals 0.481 for the calculation time. Therefore, the null hypothesis is not rejected and all three algorithms perform equally despite the longer calculation time in the proposed algorithm than the other two algorithms. In the case of spacing metric, the MOVNS-SA and NSGA-II algorithms stage equal performances that are grouped into the same category; however, the proposed algorithm outperforms the other two algorithms. In terms of diversity and MID metrics, there is no statistical difference between the performances of MOVNS-SA and NSGA-II algorithms; however, the performance of the proposed algorithm is significantly different from that of these two algorithms. With regard to the NOP solutions, the proposed algorithm and the NSGA-II algorithm perform equally; however, their performances are different from that of MOVNS-SA algorithm, resulting in fewer Pareto solutions than the other two algorithms. Therefore, it can be concluded that the proposed algorithm outperforms the other two algorithms in terms of diversity, spacing, and the MID. Moreover, the proposed algorithm and NSGA-II perform equally to the NOP solutions, outperforming the third algorithm. Although the CPU time for the proposed algorithm is longer than that for other algorithms, it is not significant. Figures 15–19 show the interval graph of algorithms for NOP, MID, spacing, time, and diversity metrics, respectively.

To evaluate the proposed algorithm, the algorithm is compared with the ε-constraint method, which is coded in GAMS. Considering the NP-hardness of the model and the non-possibility of solving the model by the ε-constraint method in larger sizes, a Pareto line is derived from the proposed algorithms with the ε-constraint method for the sample problem 7 of Table 5. First, the problem is solved using the proposed linear approximation for the first objective function, and in the next step, based on the obtained result, the value of the first objective function is calculated. Figure 20 shows the Pareto line resulting from the proposed algorithm and ε-constraint method for the sample problem 7. In this figure, the horizontal vector shows the values of the first objective function, and the vertical vector shows the value of the second objective function. As it is clear from the figure, the proposed algorithm offers better Pareto solutions than other

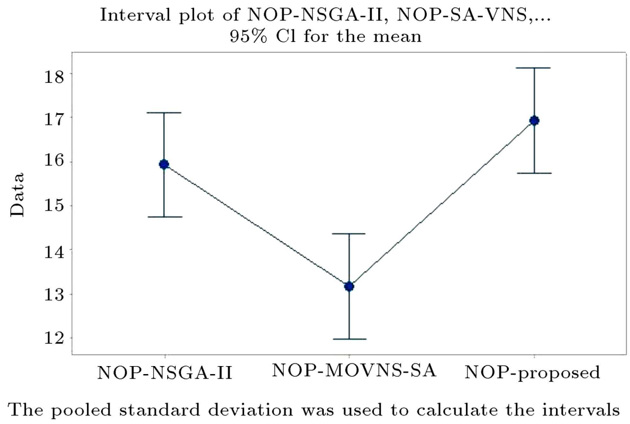

Figure 15. Interval graph of algorithms for Number Of Pareto (NOP) metric.

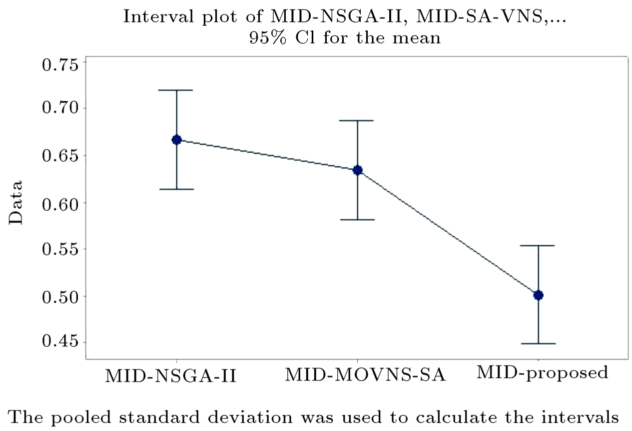

Figure 16. Interval graph of algorithms for Mean Ideal Distance (MID) metric.

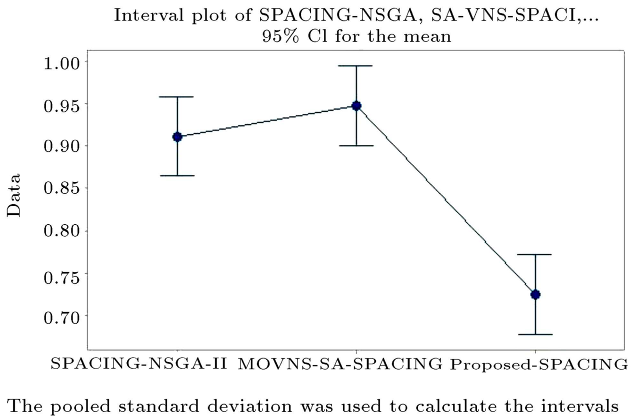

Figure 17. Interval graph of algorithms for spacing metric.

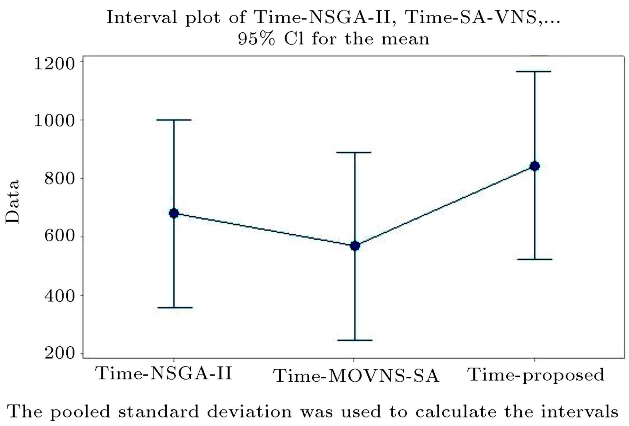

Figure 18. Interval graph of algorithms for time metric.

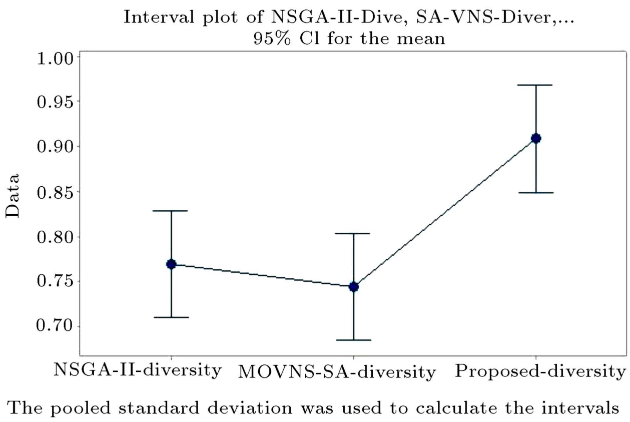

Figure 19. Interval graph of algorithms for diversity metric.

algorithms and the resulting answers are close to the ε-constraint method.

In this section, a sensitivity analysis is carried out showing how changing the determining parameters can change the results. To this end, the important parameters for the sensitivity analysis, namely the maximum budget and the maximum shortage percentage, are selected. In the sensitivity analysis, all the parameters

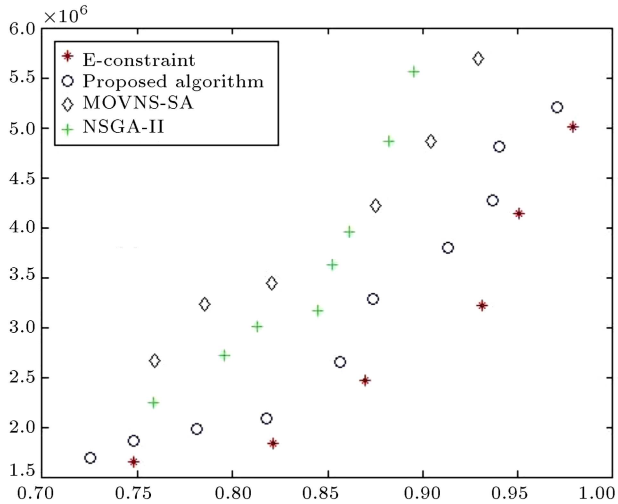

Figure 20. Pareto line for the ε-constraint method and other algorithms.

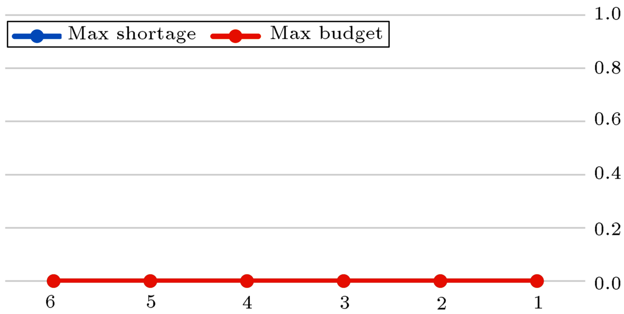

Figure 21. Sensitivity analysis of the second objective.

are considered constant. For the sensitivity analysis, problem 5, shown in Table 5, which has 4 depots, 8 points of demand, and 4 relief commodities, is used. To this end, the problem is solved using GAMS as a single-objective problem for the first- and second-objective functions. We change the parameter values from a current value of 0.6 to a value 1.4 times the current value and analyze its effect on the behavior of the objective functions. Table 10 shows the sensitivity analysis results for the above-mentioned parameters.

According to Figure 21 which shows the sensitivity analysis for the second objective function, the budget variations do not affect the quality of the second objective function, which is the cost objective function. However, this objective function shows the sensitivity to the allowable shortage percentage. In this case, the shortage cost is lower than the other costs. Hence, the costs grow with an increase in the allowable shortage coefficient. If the shortage cost of commodities increases, this trend is reversed. As a result, the costs may not decrease with an increase in the shortage coefficient.

The results of the sensitivity analysis of the first objective function, shown in Figure 22, also suggest that the budget variations do not influence the quality

Table 10. Sensitivity analysis results.

Max budget	First objective function	Second objective function	Max shortage	First objective function	Second objective function
0.6*Bu	Not acceptable	Not acceptable	0.1*d	–0.1566	4556389
0.8*Bu	–0.1566	3121494	0.2*d	–0.1566	4591357
Bu	–0.1566	3121494	0.4*d	–0.1566	1940852
1.1*Bu	–0.1566	3121494	0.6*d	–0.1053	1938446
1.2*Bu	–0.1566	3121494	0.8*d	–0.0512	1938446
1.4*Bu	–0.1566	3121494	0.9*d	–0.0512	1938582

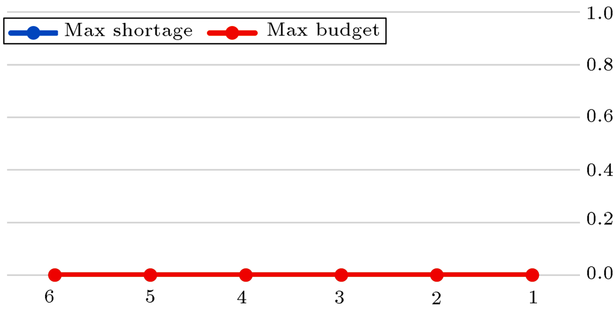

Figure 22. Sensitivity analysis of the first objective.

of the first objective function (i.e., reliability). However, this objective function is sensitive to the allowable shortage. In the proposed model, the system reopens fewer centers with an increase in the allowable shortage coefficient, thereby improving system reliability. However, after the increase in the allowable shortage, reliability coefficient growth stops and this parameter loses its effect on the first objective function.

6. Conclusion and future research

In the event of a disaster, organizing victims and sending essential commodities are the priority actions. In this respect, this study designed a forward-backward relief supply chain and developed a multi-objective model to determine the location of local warehouses and hospitals. Moreover, to improve the efficacy of the system, a multi-mode transportation system was considered to deliver commodities to the affected areas and take the injured back simultaneously to hospitals and hybrid centers. In this model, the maximization of the service level and minimization of the costs were the main objectives. As this model was NP-hard, the ε-constraint method could not work efficiently for large-scale problems. Hence, a hybrid Non-dominated Sorting Genetic Algorithm (NSGA-II) with Simulated Annealing (SA) and Variable Neighborhood Search (VNS) algorithms was developed to solve larger problems. The results of this algorithm were compared with those of MOVNS-SA and NSGA-II by five metrics, and the results indicated that the proposed algorithm outperformed other algorithms. Finally, a sensitivity analysis was considered for the maximum budget and the maximum shortage percentage. For future study, several uncertainties can be considered including the number of victims and the number of demands. Also, forming multiple scenarios related to the severity of the damages for local facilities and routes can be another suggestion. Using a different solution (e.g., meta-heuristic and hybrid exact-heuristic solutions) can be another field to be extended.

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