Socio-Economic Planning Sciences 64 (2018) 21–37

Contents lists available at ScienceDirect

Socio-Economic Planning Sciences

journal homepage: www.elsevier.com/locate/seps

An integrated location-inventory-routing humanitarian supply chain network with pre- and post-disaster management considerations

Madjid Tavana[a,b], Amir-Reza Abtahi[c,*], Debora Di Caprio[d,e], Reza Hashemi[c], Reza Yousefi-Zenouz[c]

[a] Business Systems and Analytics Department, Distinguished Chair of Business Analytics, La Salle University, Philadelphia, PA 19141, USA
[b] Business Information Systems Department, Faculty of Business Administration and Economics, University of Paderborn, D-33098 Paderborn, Germany
[c] Department of Information Technology Management, Kharazmi University, Tehran, Iran
[d] Department of Mathematics and Statistics, York University, Toronto, Canada
[e] Polo Tecnologico IISS G. Galilei, Via Cadorna 14, 39100, Bolzano, Italy

ARTICLE INFO

Keywords:
Humanitarian supply chain
Facility location
Vehicle routing
Inventory management
Multi-objective optimization

ABSTRACT

Efficiency is a key success factor in complex supply chain networks. It is imperative to ensure proper flow of goods and services in humanitarian supply chains in response to a disaster. To this end, we propose a multi-echelon humanitarian logistic network that considers the location of central warehouses, managing the inventory of perishable products in the pre-disaster phase, and routing the relief vehicles in the post-disaster phase. An epsilon-constraint method, a non-dominated sorting genetic algorithm (NSGA-II), and a modified NSGA-II called reference point based non-dominated sorting genetic algorithm-II (RPBNSGA-II) are proposed to solve this mixed integer linear programming (MILP) problem. The analysis of variance (ANOVA) is used to analyze the results showing that NSGA-II performs better than the other algorithms with small size problems while RPBNSGA-II outperforms the other algorithms with large size problems.

1. Introduction

Natural disasters have always been part of our lives. Despite the scientific and technological developments, humans are not able to prevent these events. Several catastrophes and natural disasters such as Tsunamis, floods, earthquakes, and natural disasters, have happened in the last decades. Due to fatal earthquakes in Turkey (Izmit, 1999), Taiwan (Chichi, 1999), India (Gujurat, 2001), Iran (Bam, 2003), Pakistan (Kashmir, 2004), China (Sichuan, 2008), and Haiti (2010), about 450000 people have lost their lives. The tsunami in Indonesia (2004), Katrina hurricane in the USA (2005), and the flood in Pakistan (2010) have caused the deaths of more than 300,000 people, the loss of billions of dollars of assets, and made more than 20 million people homeless [1]. Earthquakes are the most frequent of all natural disasters. The effects of strong earthquakes can be destructive. Even if thousands of networked and connected seismograph stations are installed all over the world, and the collected data is continuously analyzed by powerful computers, we are still unable to forecast the exact time and location of earthquakes. Hence, the main question to consider is "Must humans always suffer from the catastrophic consequences of earthquakes or can scientific methods prevent the losses and ruins that come with them?"

As an example consider Tehran, the capital city of Iran. This city is located in the earthquake fault area and, between 1830 and 1855, the city was destructed four times. In that period, Tehran was still a small city and the number of damaged people remained low. Nowadays, Tehran has a population of 13 million people and an earthquake would cause the death of more than 1 million people resulting in one of the most dangerous and fatal events in the history of the world. This is why one of the high priority targets of local authorities and relief organizations is to create a humanitarian relief network to prepare the city to face earthquakes.

Being prepared and knowing how to appropriately respond to a disaster is an essential part of any crisis management plan [2,3] Sprenger & Mönch [4–8]. Part of this preparation consists in designing a relief network characterized by a two-level structure: central warehouses and local distribution centers. The central warehouses, with high capacity of storing, should be located in safe places and away from earthquake fault areas. The distribution centers can be located in public places such as schools, hospitals, and mosques, usually distributed throughout the city. In order to be always prepared to face an

* Corresponding author.
E-mail addresses: tavana@lasalle.edu (M. Tavana), abtahi@khu.ac.ir (A.-R. Abtahi), dicaper@mathstat.yorku.ca (D. Di Caprio), rezahashemi69@gmail.com (R. Hashemi), reza.zenouz@gmail.com (R. Yousefi-Zenouz).
URL: http://tavana.us (M. Tavana).

https://doi.org/10.1016/j.seps.2017.12.004
Received 9 October 2017; Received in revised form 10 December 2017; Accepted 27 December 2017
Available online 30 December 2017
0038-0121/

earthquake or a natural disaster, in the absence of an adequate number of central warehouses, some of the existing public and general places can be alternatively used as central warehouses.

In humanitarian logistics, the primary actions must be taken within the first 72 h following the earthquake [43]. The first 12 h that follow the disaster are crucial and known as the standard relief time (SRT). Any kind of delay in taking the necessary actions could result in the death of more people. Public and non-public organizations have to assess the situation immediately and start sending relief products from local warehouses to damaged areas. Moreover, time constraints must be considered. An effective and efficient humanitarian logistic system should minimize human casualties by sending and delivering relief products such as food, water, and medical equipment to the damaged areas at the SRT (Perboli et al. [9–11], Goli & Alinaghian [12–14]. That is, rapidly allocating crucial and vital items is a high priority goal in the initial response to a catastrophic event. In this sense, it must be considered that local distribution centers are usually adjacent to demanding areas but they also have less capacity than central warehouses.

It is necessary to create a model able to provide the best positions for the central warehouses among the designated areas, determine the capacity of the central warehouses, and, at the same time, present the best order policy to replenish and restore the perishable products (i.e., products that must be consume within a certain time period) before a catastrophic event occurs. In particular, regarding the problem of omitting or rebuying the products in store before their expiration date, the order policy should determine per each product and in each time period, the quantity that needs to be omitted and the quantity that needs to be bought again. After determining the location of the central warehouses and the inventory control plan, depending on the position of the damaged areas, the model should be able to deliver the best relief distribution plan in order to minimize the time and cost related to the relief operations.

The model proposed in this study accounts for the issues and constraints dictated by the necessity of finding the correct location for central warehouses and conducting an inventory control for perishable products before the disaster occurs, as well as for the design of a relief distribution plan through the formulation of a multi-echelon multiple depots vehicle routing problem after the disaster has occurred. The humanitarian relief and rescue networks are designed on the basis of a mathematical mixed integer linear programming (MILP) problem.

To solve the model and determine the values of the decision variables, the Epsilon-Constraint method was used to solve small size problems. However, due to the high complexity of the problem, this method was not able to provide a solution. Therefore, the problem was coded and solved by running two meta-heuristic algorithms, the non-dominated sorting genetic algorithm-II (NSGA-II) and the reference point based non-dominated sorting genetic algorithm-II (RPBNSGA-II). Both small and large size problems were solved using the MATLAB software. Finally, the results were examined using the analysis of variance (ANOVA) through the Minitab Software.

The paper proceeds as follows. Some of the related recent literature is reviewed in Section 2. Section 3 outlines the features accounted for when formulating the proposed model, its characterizing aspects and its novelty compared to the existing literature. In Section 4, the new mathematical model is formulated and the equations described. In Section 5, outlines the meta-heuristic methods used to solve the problem, namely, RPBNSGA-II and NSGA-II. The computational results of this study are examined in Section 6. Finally, Section 7 presents the conclusion along with some suggestions for future research and practical implementations on the side of relief agencies such as the Red Crescent and the Red Cross.

2. Literature review

In this section, different aspects of the related literature are considered. Previous studies and the latest research findings in the field of disaster management are examined focusing on humanitarian logistics and the related optimization problems and solving methods.

Barzinpour & Esmaeili [1] developed a new multi-objective MILP model to shape the preparation phase of a crisis management plan. Their model was based on a real case study of an urban area in Tehran and considered both humanitarian and cost based objectives. The mathematical results indicate that using “virtual” areas helps the authorities to create better cooperation and coordination among local residents improving the efficiency of the decision-making process. Najafi et al. [15] focused on logistics management issues, that is, the transportation of relief products to the damaged areas and of injured people to hospitals. Their model allows for updated information at any time to adjust the plan accordingly. The model minimizes the total transportation time for both the people to reach a hospital and the supplies to reach the damaged areas. Experiments are designed to examine the influence of the geographical and topological properties of the network on the agility in taking actions in an earthquake situation.

Rezaei-Malek & Tavakkoli-Moghaddam [16] presented a two-objective MILP model to operationally plan humanitarian logistics. The model aims at minimizing both the average response time and the total operation cost (i.e., the fixed cost of building warehouses, the cost of preserving the unused supplies, and the cost of the unsatisfied demand forfeit) while guaranteeing optimum policies in terms of warehouse locations, emergency relief items to stock in each warehouse, and distribution plan. The model is solved using the reservation level Tchebycheff procedure (LRTP) method. Rath & Gutjahr [17] proposed a three-objective optimization model with a medium-term economic objective function, a short-term economic objective function and a humanitarian objective function. The Epsilon-Constraint method is used to obtain the Pareto frontier while every single one-objective optimization problems is solved using an exact solving method and a mathematical heuristic technique that builds on MILP. The results obtained from the mathematical heuristic method are compared with those returned by the meta-heuristic NSGA-II method.

Garrido et al. [18] aimed at optimizing both the inventory levels for supplying emergencies and vehicle availability. The flood phenomenon is represented by a stochastic time-space process. The model is solved using sample average approximation. The paper presents a method to quantitatively determine the effects of the existing logistic parameters. Zhang et al. [19] examined a location-routing problem involving warehouses that are randomly thrown into disorder. A scenario dependent MILP model is defined to optimize depot positioning, delivery routing towards faraway areas and alternative planning. The model is solved by a meta-heuristic algorithm exploiting maximum-likelihood sampling, route-reallocation improvement, two-stage neighborhood search and simulated annealing. Ahmadi et al. [9] presented a position routing model with multiple warehouses, considering possible disorders within the network (road destruction or unavailability), multiple uses of transportation vehicles and SRT. This model is generalized to a two-stage stochastic programming problem with stochastic travel time able to determine the locations of the distribution centers. Instances of small size optimization problems are solved in GAMS/CPLEX. A Variable Neighborhood Search Algorithm is created to solve the deterministic model. Onan et al. [20] proposed a framework for determining the position of temporary storage points and, in particular, planning for environmentally sustainable ways of gathering and transporting the disaster waste. A multiple objective optimization model is developed and solved by an NSGA-II algorithm, the objectives consisting of minimizing cost and vulnerability to dangerous losses.

Bastian et al. [21] proposed a multi-criteria decision analysis (MCDA) framework to optimize military humanitarian aids through air supply chains. A weighted integer programming model and an integer stochastic model are applied to optimize the network design, logistic costs, classified locations and procurement values, and inventory levels. Their framework yields an equilibrium between productivity and responses in air military supply chains. Alem et al. [22] developed a two-stage stochastic network flow to help in quickly deciding how to deliver the humanitarian aids to injured people. The model considers a set of parameters overlooked in the related literature such as budget allocation, size of the different vehicle types, procurement, and delay time changes during a dynamic multi-period horizon. The problem is solved within a reasonable computing time using a simple two-stage heuristic method that is shown to perform well for both real and random instances. Celik et al. [23] proposed a two-stage stochastic MILP model that incorporates the problems of determining the pre-location of the supplies, making decisions about the inventory level, storing for emergency procurement, and locating distribution centers. The obtained results lead to a framework that can be used by relief agencies to decide on the location and number of distribution centers in different situations. Tofighi et al. [24] considered the problem of designing a two-stage humanitarian logistic network including central warehouses and local distribution centers developing a two-stage scenario planning approach. In the first stage, the locations of central warehouses and local distribution centers are determined. In the second stage, a relief plan is developed based on different scenarios. To solve the model and find a feasible solution in a reasonable CPU time, they develop a specifically designed differential evolution (DE) algorithm.

Zhu et al. [25] used the Ant Colony Algorithm to solve the problem of coordinating the complex interactions between supplies distribution and route selection while considering important factors such as the route inadequacy and travel time uncertainty during supplies distribution. The obtained results show the effectiveness of Bayesian decision making theory in optimizing emergency logistics. Bai [26] investigated a fuzzy model to determine the allocation of emergency supplies in three-stage humanitarian logistic networks. In this model, type-2 fuzzy variables with known possibility distributions are used to represent uncertain quantities such as post-disaster acquisition and transportation costs, suppliers' orders, and demands of damaged areas. The problem is transformed into an equivalent parametric MILP model to allow for the implementation of a common algorithm/software. Fereiduni & Hamzehee [27] used multi-objective mathematical modelling and a P-robust approach to minimize the unsatisfied demands and the total costs of governments and suppliers in situations where, due to the political constraints, the government of the damaged areas refuses to accept financial aids from international agencies. The sensitivity analysis performed for the experimental results allows to estimate the effects due to the various parameters providing managerial insights.

Tavana et al. [28] focused on the problem of designing a X-bar Control Chart problem with multiple objectives often in contrast with one another. The objectives include the expected time of the remaining process in the static state, type I error, and detection power. The optimization problem is solved using both the NSGA-III and the multi-objective particle swarm optimization (MOPSO) algorithms. Moreover, DEA and the technique for order of preference by similarity to ideal solution (TOPSIS) are used to reduce the number of Pareto optimal solutions to make it manageable from the practical viewpoint. Numerical examples are used to compare NSGA-III and MOPSO solutions indicating a better performance of NSGA-III. Piasson et al. [29] presented a multiple objective model to solve the mathematical optimization problem of maintenance planning for an electric power distribution system (EPDS). They aim at minimizing preventive maintenance costs as well as maximizing the reliability indices of the whole system. The model is solved by implementing the NSGA-II algorithm. Mousavi et al. [30] defined a multi-period and multi-product inventory control model subject to budget constraint with the purpose of finding a set of Pareto optimal solutions in different time periods able to simultaneously minimize the total inventory cost and the storage space. The NSGA-II algorithm, the non-dominated ranked genetic algorithm (NRGA), and the MOPSO algorithm are implemented while the Taguchi method is applied to analyze the model solutions and compare the performances of the algorithms. The analysis indicates a considerable difference in performance in each one of the numerical examples considered.

Rezaei-Malek et al. [31] presented a multi-objective mathematical, two-stage stochastic, and mixed integer non-linear programming (MINLP) model for relief pre-location finding in crisis management. The model aims at improving the network reliability by accounting for alternative possible routing plans and it is solved using an integrated separable programming-augmented Epsilon-Constraint method. Experiments and a real case study are shown to validate the theoretical approach. The results indicate that the Epsilon-Constraint method performs better than NSGA-II in terms of solution time, but NSGA-II can solve large-scale problems. Rezaei-Malek et al. [32] proposed a new integrated model to determine the locations for the optimal allocation of relief commodities and an efficient distribution plan along with the best order policy for restoring perishable products in the pre-disaster phase. The non-deterministic nature of the problem results in using a strong stochastic scenario-based approach. Their model implicitly seeks to minimize: (1) the weighted average of action time and (2) the total operational cost in the pre-disaster phase and (3) the forfeit costs of unsatisfied demands and unused products in the post-disaster phase. The reservation level Tchebycheff procedure (RLTP) is used as an interactive approach to solve the two-objective model.

Fereiduni & Shahanaghi [33] presented a network designing model to help location and allocation decisions in humanitarian logistics when facing multiple emergency periods. The results of their study indicate that the model helps decision makers and agencies improving both humanitarian and financial objectives in the real world.

A comparison of all the aforementioned studies is outlined in Table 1.

Two interesting and quite complete surveys on logistics models for the response and recovery planning phases are provided by Özdamar & Ertem [5] and Goldschmidt & Kumar [34]. The first survey focuses on categorizing relevant models based on their modelling features and formulation structures. The technological developments allowing for the execution and solution of these models are also discussed leading to the conclusion that a standard software would be necessary in order to guarantee international collaboration and effective actions. The second survey classifies the up-to-date research in the field of humanitarian operations and crisis/disaster management based on a newly introduced lifecycle management framework with the goal of identifying areas for future research.

The literature focusing more specifically on the use of heuristics (such as NSGA-II) as solving methods for optimization problems related to humanitarian SCM is also increasing. The survey offered by Zheng et al. [35] presents the research advances in evolutionary algorithms applied to disaster relief operations with the aim of facilitating the readers to identify suitable methods in real-life situations. Among the most recent references, Seada & Deb [36], Vahdani et al. [37], Boonmee et al. [38], Swamy et al. [39], Vahdani et al. [40], Nair et al. [41], and Noham & Tzur [42] discuss the necessity of keeping developing meta-heuristic algorithms, such as NSGA-like algorithms, capable of solving emergency humanitarian logistics problems. The general goal is to increase the exiting stable of population-based search mechanisms that allow for efficient solutions while satisfying strict response time requirements.

3. Comparing the proposed disaster management approach with other recent ones

In the current paper, we consider the following issues. The simultaneous identification of these issues and their interpretation as constraints of the proposed model characterizes our study providing a novel contribution to the literature.

- Considering perishable products in the model and determining an order policy and inventory control plan according to their

Table 1
Overview of the latest relevant studies on pre- and post-disaster response modelling.

Researcher	Examined problem	Modelling method	Applied technique for solution	Main findings
Tofighi et al. [24]	Designing a two-stage humanitarian logistic network including central warehouses and local distribution centers.	MILP	Differential Evolution (DE)	Better performance of the proposed SBPSP in comparison with the existing relief network in Tehran
Rezaei-Malek et al. [32]	Determining the optimal location-allocation and distribution plan along with the best ordering policy for restoring perishable products in the pre-disaster phase.	MILP	Tchebycheff (RLTP)	Considerable saving in costs by using the strong stochastic scenario-based approach in comparison with the stochastic scenario-based approach
Ahmadi et al. [9]	Modelling multiple warehouses location considering disorders of the network (road destruction), several vehicles routing and standard relief time.	MILP	Variable Neighborhood Search Algorithm	Considerable reduction in unsatisfied demands with cost per unit of most local warehouses and vehicles
Barzinpour & Esmaeili [1]	Planning the preparation stage of a crisis management plan	MILP	Goal Programming	Aiding local authorities selecting potential areas to coordinate and cooperate better with the local residents and improving the efficiency of decision making
Najafi et al. [15]	A dynamic routing and dispatching model for planning logistic operations in the occurrence of earthquakes (transportation of products to damaged areas and transportation of injured people to hospitals)	MILP	Dynamic Dispatching and Routing Algorithm (DDRA)	Preference should be given to positioning a relatively large number of suppliers and hospitals with low capacity rather than to positioning a low number of suppliers and hospitals with high capacity
Bastian et al. [21]	A MCDA framework for optimizing the military humanitarian aids through air supply chain	MILP	Stochastic Mixed Integer Weighted Goal Programming	Increasing the average time of action and the cost of supply chain by reducing the unsatisfied demand
Garrido et al. [18]	Stochastic programming for flood emergency logistics	ILP	Sample Average Approximation	Significant differences among the solutions when varying logistic parameters such as number of products, number of periods, inventory capacity and amount of satisfying supplies, and time cost
Zhang et al. [19]	Routing problem of reliable location under disorder constraints	MILP	Local Search-Based Heuristic	Better performance of MILP in comparison to those obtained by the Gurobi Optimization software for both small and large Reliable Location Routing Problems (RLRPs). Effectiveness and efficiency of the proposed algorithm in terms of CPU and objective function value.
Rezaei-Malek & Tavakkoli-Moghaddam [16]	Planning a strong humanitarian relief logistic network	MILP	Tchebycheff (LRTP)	Application and effectiveness of the proposed model on a case study in the Seattle region in the USA
Alem et al. [22]	A new two-stage stochastic network for delivering quick humanitarian aids to injured people	MILP	Heuristic Method and CPLEX	Ability of the model of planning aids and organizing relief works to provide an appropriate service level in most scenarios. Appropriate performance of the proposed heuristic method – real and stochastic samples.
Celik et al. [23]	Decision making about the number of supplies and their location- buying in pre- and post- disaster stages as well as their allocation when facing large-scale emergencies	MILP	Genetic Algorithm	Presenting a framework for relief agencies to determine the location and number of distribution centers in different situations
Rezaei-Malek et al. [31]	Developing a multiple objective, two-stage stochastic, nonlinear and mixed integer model for relief pre-location finding in crisis management	MINLP	Epsilon-Constraint and NSGA-II	Better solution time of Epsilon-Constraint Method in comparison with NSGA-II method while generating similar high-quality solutions
Zhu et al. [25]	Optimization of emergency transportation network resources based on the Bayesian risk function		Ant Colony Algorithm	Effectiveness of the Bayesian decision-making theory in optimizing emergency logistics
Bai [26]	Pre-positioning emergency supplies considering the fuzziness of logistic parameters and a three-stage humanitarian logistic network	MILP	Ordinary Algorithms of Lingo Software	Relatively fast solutions for the proposed pre-positioning problem while allowing for the implementation of common algorithms/softwares
Fereiduni & Shahanaghi [27]	A strong optimization model for distributing and evacuating in the occurrence of natural disasters	MILP	Monte Carlo Simulation to Produce Distribution Scenarios	The proposed model helps decision makers and agencies to improve both financial and humanitarian objectives in the real-life situations
Fereiduni & Hamzehee [27]	Designing a P-robust model in humanitarian logistics in non-neutral political settings	MILP		Dominance of the proposed P-robust model on the deterministic model
Rath & Gutjahr [17]	The routing-positioning problem of warehouses in disaster relief support operations	MILP	Epsilon-Constraint Method, Math-Heuristic Technique, and NSGA-II	A considerable increase in the efficiency of Adaptive Epsilon Constraint Algorithm (AECA) using a set of constraints. A good estimation to the non-dominant set solving three objective problems with the heuristic constraint set method. Providing a method much faster than running AECA.
Tavana et al. [28]	Optimizing the multiple objective control chart		MOPSO and NSGA-III	Better and more efficient performance of NSGA-III in producing optimized solutions
Piasson et al. [29]	Maintenance planning based on reliability of electric power distribution systems		NSGA-II	Quality of the proposed method for maintenance planning in EDPS

(continued on next page)

Table 1 (*continued*)

Researcher	Examined problem	Modelling method	Applied technique for solution	Main findings
Mousavi et al. [30]	A multi-product and multi-period seasonal inventory control model subject to budget constraint (inventory costs under the inflation and discount policy).		MOPSO, NSGA-II, and NRGA	Considerable differences in performance criteria for each of the three numerical examples examined.
Onan et al. [20]	Development of a multi-objective optimization method for managing disaster losses.	BLP	NSGA-II	Less complexity of the algorithms and developmental multi-objective methods

consumption time.

- Considering the capacity limits of different routes in the transportation network.
- Allowing for the possibility of transporting products and cross transportation among different local distribution centers to reduce the unsatisfied demand.
- Considering time and cost of loading and unloading at the hospitals.
- Allowing for vehicle re-usage by formulating an integrated model that combines the vehicle routing problem (VRP) with the multi-echelon vehicle routing problem (MEVRP) and multiple depot vehicle routing problem (MDVRP). In this research, multi-echelon routing contains two echelons: in the first echelon, central warehouses are considered as depots and local distribution centers are considered as customers; in the second echelon, local distribution centers are considered as depots and the demand points of relief products are considered as customers. Moreover, due to the large amount of central warehouses and local distribution centers, the problem also belongs to the class of multiple depot vehicle routing problems.
- Using RPBNSGA-II for solving the problem

Table 2 compares our study with other recent relevant studies described in the literature review section outlining several innovative aspects that characterize the proposed model.

4. Problem definition

This section is articulated in three subsections. In the first subsection, the structure of the problem and the related logistic network are explained. The second subsection presents the problem assumptions. The third subsection describes the new mathematical formulation.

4.1. Problem structure

This study focuses on a particular type of disaster, earthquakes. Thus, the problem specifications and parameters have been determined by benchmarking the urban area of Tehran, which is located on an earthquake fault. Following the literature and considering the geographical position of the city of Tehran, designated local warehouses should be located somewhere away from the cracks and also at a reasonable distance from the points of the city more vulnerable to disaster. Therefore, the margin points of Tehran have been considered as central warehouses. The existing hospitals in the city have also been considered as relief and treatment agencies along with the local distribution centers for dispatching relief products to the damaged areas. Fig. 1 illustrates an example of possible design for a logistic network to use in a disaster management plan.

The model is divided into two stages. The first stage concerns the phase before the earthquake occurs and includes deciding the location of central warehouses, buying and transporting resources from suppliers to central warehouses, and determining the optimal order policy to regulate both the buying of perishable products to be stored in the warehouses and the selling of those already stored before their expiration date and in different time periods. In this regard, after determining the location of the central warehouses and the optimal order policy, the required time duration of each product that should be stored in the warehouses is established. Hence, the following buying/selling procedure is applied: a product is bought or kept stored in a warehouse if its required time duration does not exceed its expiration date; a product, already stored in a warehouse, is removed and sold if its required time duration exceeds its expiration date.

The second stage deals with the phase after the earthquake has occurred. After the earthquake, relief groups should deliver relief items, such as food, water, and medical kits, to hospitals and damaged areas. In order to minimize the time and cost of the operations, the logistic problem represented by the transportation of relief products is

Table 2
Comparison of the latest relevant studies with the proposed one.

Paper	Model		Solution method	Planning time		Location	Routing			Inventory control	Saved commodities			Objective functions	
	Modelling method	Objective		Pre-disaster	Post-disaster		VRP	MDVRP	MEVRP		Perishable	Multi-period	Multiple	Loading & unloading time	Loading & unloading cost
Zhu et al. [25]		Minimize transportation loss & all emergency supplies	Ant Colony Algorithm		*										
Alem et al. [22]	MILP	Minimize pre- & post-disaster cost	Heuristic Method & CPLEX	*	*							*	*		
Barzinpour & Esmaeili [1]	MILP	Reduce cost & decrease population coverage	Goal Programming Approach	*		*							*		
Bastian et al. [21]	MILP	Reduce time, budget and demand coverage	Stochastic, Mixed Integer, Weighted Goal Programming		*	*									
Onan et al. [20]	BLP	Minimize post-disaster cost & population risk	NSGA-II		*	*									
Bai [26]	MILP	Minimize pre- & post-disaster cost	Common methods of lingo	*	*	*									
Rezaei-Malek & Tavakkoli-Moghaddam [16]	MILP	Minimize pre- & post-disaster cost & post-disaster time	LRTP	*	*	*							*		
Celik et al. [23]	MILP	Minimize pre- & post-disaster cost	Genetic Algorithm	*	*	*							*		
Rezaei-Malek et al. [31]	MINLP	Minimize pre- & post-disaster cost	Epsilon-Constraint & NSGA-II	*	*	*							*		
Fereiduni & Hamzehee [27]	MILP	Minimize unsatisfied demand & post-disaster cost			*	*						*	*		
Fereiduni & Shahanaghi [27]	MILP	Minimize pre- & post-disaster cost	Monte carlo simulation	*	*	*						*	*		
Tofighi et al. [24]	MILP	Minimize pre- & post-disaster cost & post-disaster time	Exact Method & DE	*	*	*				*			*		
Garrido et al. [18]	ILP	Minimize post-disaster cost	Sample Average	*	*					*		*	*		
Ahmadi et al. [9]	MILP	Minimize post-disaster time & cost	Variable Neighborhood Search Algorithm		*	*	*	*					*		
Najafi et al. [15]	MILP	Reduce waiting time and delay at post-disaster areas	Dynamic Dispatching and Routing Algorithm (DDRA)		*		*	*					*		
Zhang et al. [19]	MILP	Minimize pre- & post-disaster cost	Local Search-Based Heuristic	*	*	*	*	*							
Rath & Gutjahr [17]	MILP	Minimize pre- & post-disaster cost & Maximize demand coverage	Epsilon-Constraint, Math-Heuristic Technique (constraint pool heuristic) & NSGA-II		*	*	*	*		*					
Rezaei-Malek et al. [32]	MILP	Minimize pre- & post-disaster cost	RLTP	*	*	*				*	*	*	*		
This paper (Our study)	MILP	Minimize pre- & post-disaster cost & post-disaster time	Epsilon-Constraint, NSGA-II, RPBNSGA II	*	*	*	*	*	*	*	*	*	*	*	*

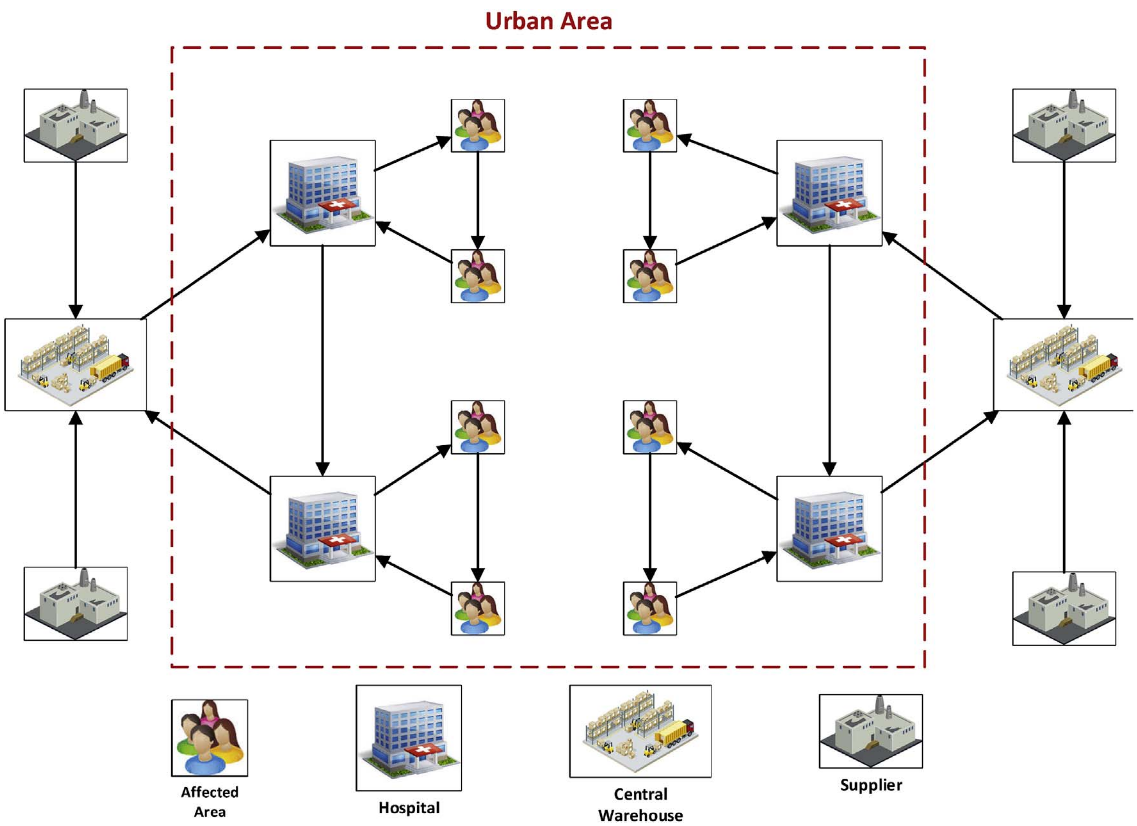


Fig. 1. Design of the considered logistics network.

modelled as a multi-echelon multi-depot vehicle routing problem (MEMDVRP). In the first echelon, the optimal routing relative to the transportation between central warehouses and hospitals should be determined. Then, in the second echelon, the optimal routing for the transportation between hospitals and damaged areas should be determined. So, first of all, it is necessary to determine the demand of each hospital for each relief product. The demand of a hospital for a product is given by the total demand of the damaged points that should be served by that hospital and the consuming demand of the hospital itself for that product.

4.2. Model assumptions

The assumptions considered in designing the model are the following:

- All relief items are perishable and it is necessary to refurbish them using an order policy.
- The capacity of the designated central warehouses has multiple levels.
- The storing equipment is vulnerable to damages.
- The network routes differ in physical conditions and the travel time relative to each route reflects the corresponding traffic condition.
- The capacity of the transportation routes is limited.
- Vehicles have different capacities.

4.3. The proposed mathematical model

In this section, first, the index sets, parameters, and variables of the model are explained. Then, the mathematical programming model is presented. Tables 3–5 show the index sets, parameters, and variables of the model, respectively: each symbol is accompanied by a short description.

The proposed mathematical model consists of three objective functions and 43 constraints that have been formalized as follows:

Table 3
Index sets.

Symbol	Description
V_o	Set of candidate warehouses
V_h	Set of hospitals
V_c	Set of demand points (i.e., affected areas)
K	Total number of product types
k	One of the possible product types: $k \in \{1, ..., K\}$ or, to simplify notations, $k \in K$
T	Total number of time periods before the disaster occurs
t	One of the possible time periods: $t \in \{1, ..., T\}$ or, to simplify notations, $t \in T$
R_k	Total number of remaining lifetime periods (i.e., till the expiration date) of product type k
r_k	One of the possible remaining lifetime periods of product type k: $r_k \in \{1, ..., R_k\}$ or, to simplify notations, $r_k \in R_k$

$$\min z_1 = \sum_{l\in V_o} f_l y_l + \sum_{k\in K}\sum_{l\in V_o}\sum_{t\in T}\left[\sum_{r_k=1}^{\beta_k} CE_k b_{kltr_k} + \sum_{r_k=\alpha_k}^{R_k} CP_{kr_k} R_{kltr_k} + \sum_{r_k=\alpha_k}^{R_k} CM_{kl} R_{kltr_k} + \sum_{r_k=1}^{R_k} CK_{kl} I_{kltr_k} - \sum_{r_k=1}^{\beta_k} IN_{kr_k} b_{kltr_k} + SP_k E_{klt}\right] \tag{1}$$

$$\min z_2 = \sum_{t\in T}\sum_{l\in V_o}\sum_{\substack{i,j\in V_o\cup V_h,\\ i\neq j}} c_{ij} x^{l}_{ijt} + \sum_{t\in T}\sum_{h\in V_h}\sum_{\substack{i,j\in V_h\cup V_c,\\ i\neq j}} c_{ij} g^{h}_{ijt} + \sum_{k\in K}\sum_{h\in V_h} s_h d_{hk} + \sum_{t\in T}\left[\sum_{l\in V_o}\sum_{k\in K} CH_k m_{lkt} + \sum_{h\in V_h}\sum_{k\in K} \tau_{hk} w_{hkt}\right] \tag{2}$$

Table 4
Parameters.

Symbol	Description
f_l	fixed cost for establishing warehouse l
CH_k	additional unit holding penalty of product type k
τ_{hk}	unit penalty cost of unsatisfied demand of product type k for hospital h
CE_k	unit removal cost for product type k
CP_{kr_k}	unit purchase cost for product type k with r_k remaining lifetime periods
CM_{kl}	unit cost for transporting product type k to warehouse l before the disaster occurs
CK_{kl}	unit cost for storing product type k in warehouse l
IN_{kr_k}	sale income per unit of product type k with r_k remaining lifetime periods
SP_k	unit penalty cost for shortage of product type k in the pre-disaster phase
β_k	total number of acceptable remaining lifetime periods for product type k before it is removed from warehouses
α_k	total number of acceptable remaining lifetime periods for product type k to be purchased
c_{ij}	cost of transportation (movement) between tow nodes i, j
S_h	unit cost for loading and unloading product type k in hospital h
TM_{ij}	time of transportation (movement) between tow nodes i, j
TU	unit loading and unloading time of product type k
dh_{hk}	demand of product type k to be utilized in hospital h
dc_{jk}	demand of product type k to be sent to demand point (affected area) j
V_k	capacity of the vehicles of the 1st level for product type k
U_k	capacity of the vehicles of the 2nd level for product type k
ϕ_{hk}	tolerable proportion of shortage of product type k at hospital h
m^1	number of 1st level vehicles
m^2	number of 2nd level vehicles
m_l^1	maximum number of 1st level routes starting from warehouse l
m_h^2	maximum number of 2nd level routes starting from hospital h
B	available budget for establishing warehouses
γ_{lk}	holding capacity of warehouse l for product type k
e_k	available amount of product type k for pre-positioning
mq_k	minimum amount of product type k that should be stocked in the warehouses
M	a sufficiently large number
ρ_{lk}	proportion of pre-positioned product type k at warehouse l remaining usable

Table 5
Variables.

Symbol	Description
y_l	1, if warehouse l is opened; 0, otherwise
m_{lkt}	Amount of unused product type k in warehouse l if earthquake strikes at time period t
w_{hkt}	shortage of product type k at hospital h if earthquake strikes at time period t
wh_{hkt}	shortage of product type k for utilization at hospital h if earthquake strikes at time period t
wc_{jkt}	shortage of product type k at demand point (affected area) j if earthquake strikes at time period t
b_{kltr_k}	amount of product type k, with r_k remaining lifetime periods, removed from warehouse l at time period t
R_{kltr_k}	amount of product type k, with r_k remaining lifetime periods, purchased for warehouse l at time period t
I_{kltr_k}	stock level of product type k, with r_k remaining lifetime periods, held at warehouse l at time period t
q_{lk}	amount of product type k held at warehouse l *(in the first time period)*
E_{klt}	shortage of product type k at warehouse l at time period t
d_{hk}	total demand of product type k at hospital h
x_{ijt}^l	1, if the 1st-level arc (i, j) is used by the 1st-level routing starting from warehouse l when earthquake strikes at time period t; 0, otherwise
g_{ijt}^h	1, if the 2nd-level arc (i, j) is used by the 2nd-level routing starting from hospital h when earthquake strikes at time period t; 0, otherwise
zf_{lh}	1, if the hospital h is served by the warehouse l; 0, otherwise
z_{hj}	1, if the demand point (affected area) j is served by the warehouse h; 0, otherwise

$$\min z_3 = \sum_{t\in T}\sum_{l\in V_o}\sum_{\substack{i,j\in V_o\cup V_h,\\ i\neq j}} TM_{ij}x_{ijt}^l + \sum_{t\in T}\sum_{h\in V_h}\sum_{\substack{i,j\in V_h\cup V_c,\\ i\neq j}} TM_{ij}g_{ijt}^h + \sum_{k\in K}\sum_{h\in V_h} TUd_{hk} \tag{3}$$

s.t.:

$$b_{kltr_k} \le I_{kltr_k};\ \forall\ k\in K,\ l\in V_o,\ t\in\{2,\dots,T\},\ r_k\in\{1,\dots,\beta_k\} \tag{4}$$

$$I_{klt+1r_k-1} = I_{kltr_k} - b_{kltr_k};\ \forall\ k\in K,\ l\in V_o,\ t\in\{2,\dots,T\},\ r_k\in\{1,\dots,\beta_k\} \tag{5}$$

$$I_{kltr_k} = R_{kltr_k} + I_{klt-1r_k+1};\ \forall\ k\in K,\ l\in V_o,\ t\in\{2,\dots,T\},\ r_k\in\{\alpha_k,\dots,R_k\} \tag{6}$$

$$I_{klt+1r_k-1} = R_{klt+1r_k} + I_{kltr_k} - b_{kltr_k};\quad \forall\ k\in K,\ l\in V_o,\ t\in\{2,\dots,T\},\ r_k\in\{2,\dots,R_k\} \tag{7}$$

$$I_{kltr_k} = 0;\ \forall\ k\in K,\ l\in V_o,\ t\in T,\ r_k\in\{1,\dots,\beta_k\} \tag{8}$$

$$\sum_{r_k=\alpha_k}^{R_k} I_{kltr_k} = \sum_{r_k=\alpha_k}^{R_k} R_{kltr_k} + \sum_{r_k=\alpha_k}^{R_k} I_{klt-1r_k} - \sum_{r_k=\alpha_k}^{R_k} b_{klt-1r_k};\quad \forall\ k\in K,\ l\in V_o,\ t\in\{2,\dots,T\} \tag{9}$$

$$\sum_{r_k=\alpha_k}^{R_k} I_{kltr_k} = q_{lk};\ t=1,\ \forall\ k\in K,\ l\in V_o \tag{10}$$

$$E_{klt} = q_{lk} - \sum_{r_k=\alpha_k}^{R_k} I_{kltr_k};\ \forall\ k\in K,\ l\in V_o,\ t\in\{2,\dots,T\} \tag{11}$$

$$R_{kltr_k} = I_{kltr_k};\ t=1,\ \forall\ k\in K,\ l\in V_o,\ r_k\in\{\alpha_k,\dots,R_k\} \tag{12}$$

$$\sum_{l\in V_o} f_l y_l \le B \tag{13}$$

$$q_{lk} \le y_l\gamma_{lk};\ \forall\ l\in V_o,\ k\in K \tag{14}$$

$$\sum_{l\in V_o} q_{lk} \le e_k;\ \forall\ k\in K \tag{15}$$

$$\sum_{l\in V_o} q_{lk} \ge mq_k;\ \forall\ k\in K \tag{16}$$

$$d_{hk} = \sum_{l\in V_o} dh_{hk}zf_{lh} + \sum_{j\in V_c} dc_{jk}z_{hj};\ \forall\ k\in K,\ h\in V_h \tag{17}$$

$$w_{hkt} = \sum_{l\in V_o} wh_{hkt}zf_{lh} + \sum_{l\in V_o} wc_{jkt}z_{hj};\ \forall\ k\in K,\ h\in V_h,\ t\in T \tag{18}$$

$$w_{hkt} + \sum_{l\in V_o}\sum_{i\in V_o\cup V_h} V_k x_{ijt}^l = d_{hk};\ \forall\ k\in K,\ h\in V_h,\ j\in V_h,\ t\in T \tag{19}$$

$$\sum_{j\in V_h} V_k x_{ljt}^l + m_{lkt} = \sum_{r_k=1}^{R_k} I_{kltr_k}\rho_{lk};\ \forall\ k\in K,\ l\in V_o,\ t\in T \tag{20}$$

$$w_{hkt} \le \varphi_{hk}d_{hk};\ \forall\ h\in V_h,\ k\in K,\ t\in T \tag{21}$$

$$\sum_{j\in V_h} x_{ljt}^l \le m_l^1;\ \forall\ l\in V_o,\ t\in T \tag{22}$$

$$\sum_{l\in V_o}\sum_{j\in V_h} x_{ljt}^l \le m^1;\ \forall\ t\in T \tag{23}$$

$$\sum_{j\in V_h} x_{ljt}^l = \sum_{j\in V_h} x_{jlt}^l;\ \forall\ l\in V_o,\ t\in T \tag{24}$$

$$x_{iht}^l \le zf_{lh};\ \forall\ i\in V_o\cup V_h,\ h\in V_h,\ l\in V_o,\ t\in T \tag{25}$$

$$x_{hit}^l \le zf_{lh};\ \forall\ i\in V_o,\ h\in V_h,\ l\in V_o,\ t\in T \tag{26}$$

$$\sum_{i\in V_h\cup V_o} x_{iht}^l = zf_{lh};\ \forall\ h\in V_h,\ l\in V_o,\ t\in T \tag{27}$$

$$\sum_{i \in V_h \cup V_o} x_{hit}^l = zf_{lh};\ \forall\ h \in V_h,\ l \in V_o,\ t \in T \tag{28}$$

$$\sum_{i \in V_h \cup V_o} \sum_{j \in V_h \cup V_o} x_{ijt}^l \le M \sum_{h \in V_h} x_{lht}^l;\ \forall\ l \in V_o,\ t \in T \tag{29}$$

$$\sum_{l \in V_o} zf_{lh} = 1;\ \forall\ h \in V_h \tag{30}$$

$$wc_{jkt} + \sum_{h \in V_h} \sum_{i \in V_h \cup V_c} U_k g_{ijt}^h = dc_{jk};\ \forall\ k \in K,\ j \in V_c,\ t \in T \tag{31}$$

$$\sum_{j \in V_c} g_{hjt}^h \le m_h^2;\ \forall\ h \in V_h,\ t \in T \tag{32}$$

$$\sum_{h \in V_h} \sum_{j \in V_c} g_{hjt}^h \le m^2;\ \forall\ t \in T \tag{33}$$

$$\sum_{j \in V_c} g_{hjt}^h = \sum_{j \in V_c} g_{jht}^h;\ \forall\ h \in V_h,\ t \in T \tag{34}$$

$$g_{ijt}^h \le z_{hj};\ \forall\ i \in V_c \cup V_h,\ j \in V_c,\ h \in V_h,\ t \in T \tag{35}$$

$$g_{jit}^h \le z_{hj};\ \forall\ i \in V_h,\ j \in V_c,\ h \in V_h,\ t \in T \tag{36}$$

$$\sum_{i \in V_h \cup V_c} g_{ijt}^h = z_{hj};\ \forall\ j \in V_c,\ h \in V_h,\ t \in T \tag{37}$$

$$\sum_{i \in V_h \cup V_c} g_{jit}^h = z_{hj};\ \forall\ j \in V_c,\ h \in V_h,\ t \in T \tag{38}$$

$$\sum_{i \in V_h \cup V_c} \sum_{j \in V_h \cup V_c} g_{ijt}^h \le M \sum_{j \in V_c} g_{hjt}^h;\ \forall\ h \in V_h,\ t \in T \tag{39}$$

$$\sum_{i \in V_h} z_{ij} = 1;\ \forall\ j \in V_c \tag{40}$$

$$\sum_{j \in V_c} z_{hj} \le M \sum_{l \in V_o} zf_{lh};\ \forall\ h \in V_h \tag{41}$$

$$g_{hjt}^h \le \sum_{l \in V_o} \sum_{i \in V_o \cup V_h} x_{hit}^l;\ \forall\ j \in V_c,\ h \in V_h,\ t \in T \tag{42}$$

$$\sum_{i,j \in V_o \cup V_h, i \ne j} \sum_{t \in T} x_{ijt}^l \le My_l;\ \forall\ l \in V_o \tag{43}$$

$$y_l,\ x_{ijt}^l,\ g_{ijt}^h,\ z_{hj},\ zf_{lh} \in \{0,1\};\ \forall\ l \in V_o,\ h \in V_h,\ i, j \in V_o \cup V_h \cup V_c,\ t \in T \tag{44}$$

$$m_{lkt},\ w_{hkt},\ wh_{hkt},\ wc_{jkt},\ b_{kltr_k},\ R_{kltr_k},\ I_{kltr_k},\ q_{lk},\ E_{klt}\ \text{nonnegative integers}\ \forall\ l \in V_o,\ h \in V_h,\ i, j \in V_o \cup V_h \cup V_c,\ t \in T,\ k \in K,\ r_k \in R_k \tag{45}$$

4.3.1. Objective functions

The proposed mathematical model has three objectives. The first and second objective functions are cost minimizing while the third objective function is time minimizing. A more detailed description of the objective functions is given below.

The first objective function, Eq. (1), seeks to minimize the total cost of procurement and preparation before the disaster occurs. This cost includes the costs of creating warehouses, warehousing, and transporting as well as those related to the inventory control of perishable products. More precisely, the first summation expression shows the total cost of creating the central warehouses. The second summation expression (1st sub-summation in square brackets) accounts for the total cost of removing products whose remaining lifetime (time remaining till the expiration date) is less than or equal to β_k. The third summation expression (2nd sub-summation in square brackets) represents the purchase cost of products whose remaining lifetime is at least α_k. The fourth summation expression (3rd sub-summation in square brackets) represents the transportation cost of products whose remaining lifetime is at least α_k. The transportation cost includes the cost of transporting the products from the supplier place till the central warehouses. The fifth summation expression (4th sub-summation in square brackets) represents the total cost of storing each merchandise unit. The sixth summation expression (5th sub-summation in square brackets) computes the total revenue gained from selling products with a remaining lifetime less than or equal to β_k and products that have been removed from the warehouses. Finally, the seventh summation expression (6th sub-summation in square brackets) corresponds to the total cost deriving from the shortage of each merchandise in the store in the pre-disaster phase.

The second objective function, Eq. (2), seeks to minimize the total relief operational cost in the action (facing) phase after the disaster has occurred. This cost includes transportation, loading and unloading costs as well as merchandise deficiency costs and unused merchandise costs. Therefore, the first summation expression indicates the total transportation costs of relief products from central warehouses to hospitals. The second summation expression indicates the total transportation costs of relief products from hospitals to damaged areas. The third summation expression indicates the total loading and unloading costs of relief products at hospitals. The fourth summation expression (1st sub-summation in square brackets) represents the total cost of unused merchandises in warehouses. The fifth summation expression (2nd sub-summation in square brackets) represents the total shortage cost of relief products in the post-disaster phase.

The third objective function, Eq. (3), seeks to minimize the total operational relief time in the action phase after the disaster has occurred. This time includes transportation, loading and unloading time. More precisely, the first summation expression accounts for the total transportation time of relief products from central warehouses to hospitals. The second summation expression accounts for the total transportation time of relief products from hospitals to damaged areas. The third summation expression accounts for the total loading and unloading time of relief products at hospitals.

4.3.2. Constraints

The constraints of the model can be grouped into three classes:

I) constraints relative to the creation of warehouses and warehousing (these constraints are necessary to model the procurement and preparation phase);
II) constraints relative to the routing of transportation vehicles (these constraints intervene in the action phase);
III) constraints relative to the type and sign of the decision variables.

4.3.2.1. Constraints of the procurement and preparation phase. Eq. (4) assures that the amount of products removed from a warehouse does not exceed that existing in the same warehouse. Eq. (5) assures that the difference between the amount of a certain product existing in a warehouse and that removed from the same warehouse in one period is balanced by its inventory for the next period. Eq. (6) requires the difference between the existing amount of a certain product and the amount bought of the same product in one period to be balanced by its inventory in the previous period. Eq. (7) balances the difference between the existing amount of a certain product and the amount bought in one period with the difference between the existing amount of the same product and the amount removed in the previous period. Eq. (8) requires the inventory of the amount of product type k with remaining lifetime less than or equal to β_k to be 0. Eq. (9) balances the total amount of both existing and bought products having remaining lifetime greater than or equal to α_k in one period with the total amount of both existing and removed products with remaining lifetime greater than or equal to α_k in the previous period. Eq. (10) assures the inventory of all the products with remaining lifetime at least α_k in the first period to be equal to the pre-determined amount that must be stored in the first period.

Eq. (11) assures the balance between the inventory of all the products with remaining lifetime at least α_k in the second period and the shortage of products relative to the pre-determined amount to be held in the first period. Eq. (12) assures the equality between the purchased and the existing amount of products in the store in the first period. Eq. (13) assures that the cost of creating central warehouses does not exceed the pre-determined budget. Eq. (14) assures that the pre-determined amount of a certain product to be held in a warehouse in the first period does not exceed the holding capacity of the warehouse for that product. Eq. (15) assures that the total pre-determined amount of a certain product to be held in the different warehouses in the first period does not exceed the available amount of that product in the market. Eq. (16) requires the total pre-determined amount of a certain product to be held in the different warehouses in the first period to be greater than or equal to the least amount of that product in the warehouses.

4.3.2.2. Constraints of the action phase. Eq. (17) determines the total demand of each hospital for each product to be used in the hospital itself and to be dispatched to the damaged points served by the hospital. Eq. (18) determines the total shortage of each hospital for each product to be used in the hospital itself and to be dispatched to the damaged points served by the hospital. Eq. (19) indicates that the total demand of each hospital for each product must be equal to the amount of products dispatched to that hospital to compensate for the total shortage for that product at that hospital. Eq. (20) indicates that the number of products dispatched by each warehouse as well as the number of unused products in that warehouse must be equal to the total usable ratio of that product in that warehouse.

Eq. (21) assures that the shortage of a certain product does not exceed the tolerable shortage for that product to meet the demand. Eq. (22) assures that the number of working routes starting from warehouse l does not exceed the maximum number of routes in level 1 starting from warehouse l. Eq. (23) assures that the total number of working routes in level 1 does not exceed the vehicle capacity of level 1. Eq. (24) requires that all the routes starting from warehouse l go back to warehouse l. Eqs. (25) and (26) assure that the routes arriving at and leaving from hospital h are part of the routes that start from warehouse l if the demand of hospital h is supplied through warehouse l. Eq. (27) assures that the total number of routes entering hospital h that have started from warehouse l is equal to 1 if the demand of hospital h is supplied through warehouse l. Eq. (28) assures that the total number of routes exiting from hospital h that have started from warehouse l is equal to 1 if the demand of hospital h is supplied through warehouse l. Eq. (29) requires all the routes existing from warehouse l at level 1 to be working if the route from warehouse l to the first hospital is working. Eq. (30) requires that each demand for each hospital is supplied by only one warehouse.

Eq. (31) requires the demand of each damaged point for each product to be equal to the number of products dispatched to that point to compensate for the shortage of that product at that point. Eq. (32) assures that the number of working routes starting from hospital h does not exceed the maximum number of routes in level 2 starting from hospital h. Eq. (33) assures that the total number of working routes in level 2 starting from hospital h does not exceed the vehicle capacity of level 2. Eq. (34) requires all the routes starting from hospital h to return to hospital h. Eqs. (35) and (36) assure that the routes arriving at and leaving from damaged point j are part of the routes that leave from hospital h if the demand of point j is supplied by hospital h. Eq. (37) assures that the total number of routes entering damaged point j that have started from hospital h is equal to 1 if the demand of point j is supplied by hospital h. Eq. (38) assures that the total number of routes exiting from damaged point j that have started from hospital h is equal to 1 if the demand of point j is supplied by hospital h. Eq. (39) requires all the routes existing from hospital h in level 2 to be working if the route from hospital h to the first damaged point is working. Eq. (40) assures that each demand of each damaged point is supplied by only one hospital. Eqs. (41) and (42) guarantee that the demand for a damaged point is supplied by a hospital only if that hospital has already been supplied by a warehouse. Eq. (43) guarantees that the demand of a hospital is supplied by a warehouse only if that warehouse has already been created.

4.3.2.3. Constraints of the decision variables. Eq. (44) shows all the variables whose values must be either 0 or 1. Eq. (45) lists all the variables taking nonnegative integer values.

5. Solution method

This section illustrates the method implemented to solve the proposed model using NSGA-II and RPBNSGA-II. First, the solution structure is described. Hence, the steps of the algorithms are outlined. Finally, the technique followed to handle the constraints is sketched.

5.1. Implementing NSGA-II

5.1.1. Structure of the solution

NSGA-II is a genetic algorithm to optimally solve multi-objective problems. The aim of this algorithm is to produce a population of solutions. Each member of the population represents a solution for the proposed mathematical model and includes:

- the route of each vehicle from each warehouse to the designated hospitals for aiding at level 1;
- the route of each vehicle from each hospital to the designated damaged points for aiding at level 2;
- the minimum amount of each product type that must be stored in each warehouse;
- the inventory of each product type with any amount of remaining lifetime periods for each warehouse and each time period.

After calculating the values of the other dependent variables characterizing each population, it is possible to find the values of the objective functions as outlined in the next section.

5.1.2. Stages of the algorithm

In this section, the stages of the algorithm are described.

- To start, an initial population, called the “main” population, is produced: each member of this population is considered as a chromosome and has the characteristics mentioned in the previous section.
- In the next stage, some members of the main population are chosen as parents and by running crossover for each couple of the chosen sub-population, a new population, called the “children population”, is created.
- Next, some members of the main population are chosen to undergo to mutations and produce a new population called the “mutated population”.
- Then, all three populations (i.e., the main, the children, and the mutated populations) are merged together to produce the “merged population”.
- The merged population is sorted using non-dominated sorting, and the set of front objective functions is determined. Then, the non-dominated solutions in each response are sorted downward using the crowding distance.
- At this point, the next iteration starts: the first front of the sorted population is chosen as the main population of the next iteration. The first front produced by this second iteration will become the main population of the third iteration and so on.
- The algorithm ends if the stopping criteria are satisfied, otherwise the next iteration is run. The stopping criteria are two: attaining a

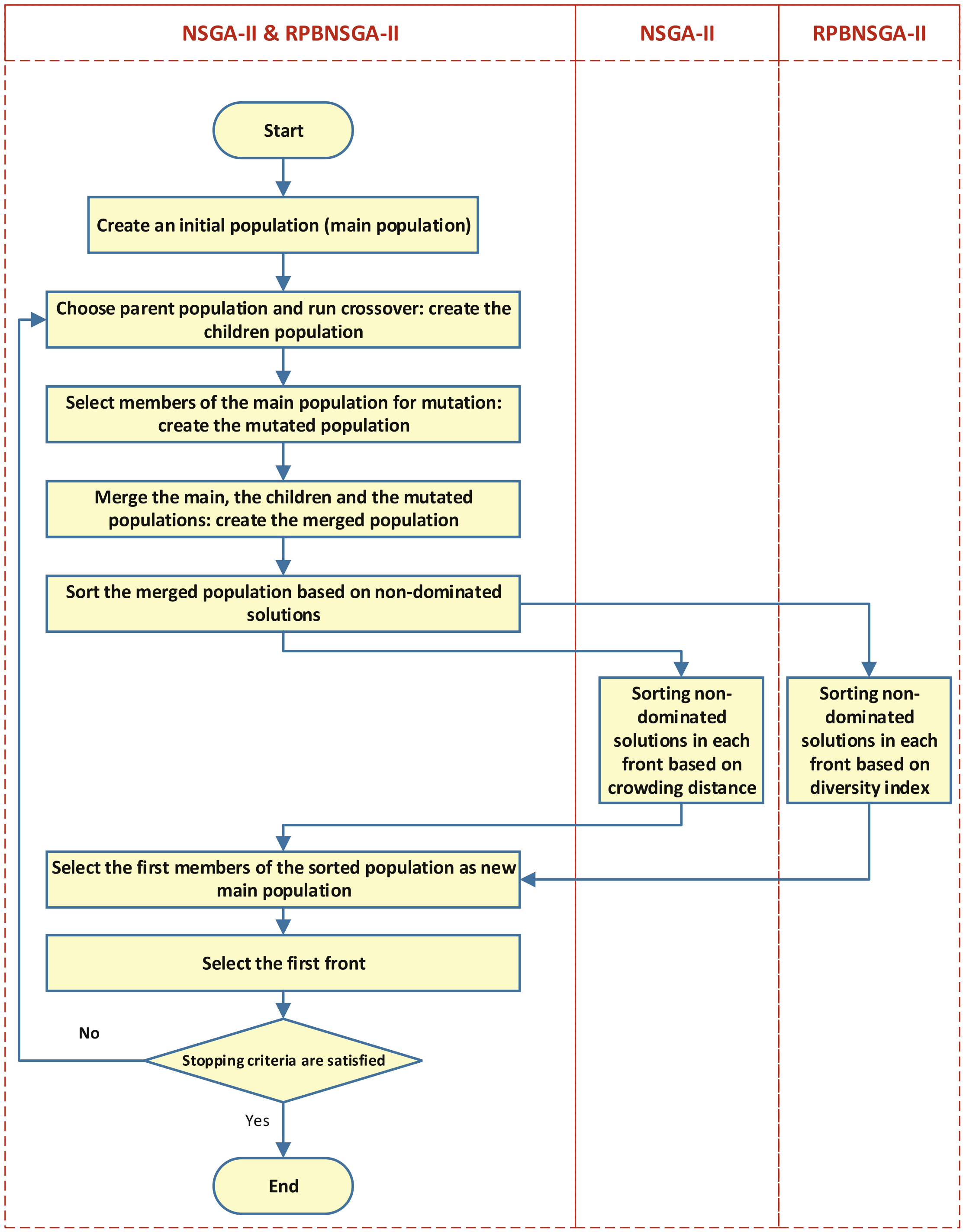


Fig. 2. The stages of NSGA-II and RPBNSGA-II.

predetermined number of iterations; attaining a predetermined number of non-dominated solutions. The algorithm ends as soon as either one of these two predetermined numbers is reached.

5.2. Implementing RPBNSGA-II

The stages and structure of the solution when running RPBNSGA-II are similar to those of NSGA-II, but the members of each front are sorted using the diversity index instead of the crowding distance.

First, for each objective function, some reference points are determined. Hence, considering the diversity criterion, the variance among the reference points increases when passing to the next objective function. Accordingly, if the number of solutions in a certain set of reference points is smaller than the number of solutions in a different set of reference points, then the former solutions dominate the latter in creating a front. That is, interpreting diversity as based on the number of solutions among the reference points, the smaller is the number of solutions among the reference points, the higher is the importance of the solutions.

The stages of both NSGA-II and RPBNSGA-II are outlined in Fig. 2. Fig. 3 illustrates the algorithm applied to determine the reference points to use in RPBNSGA-II.

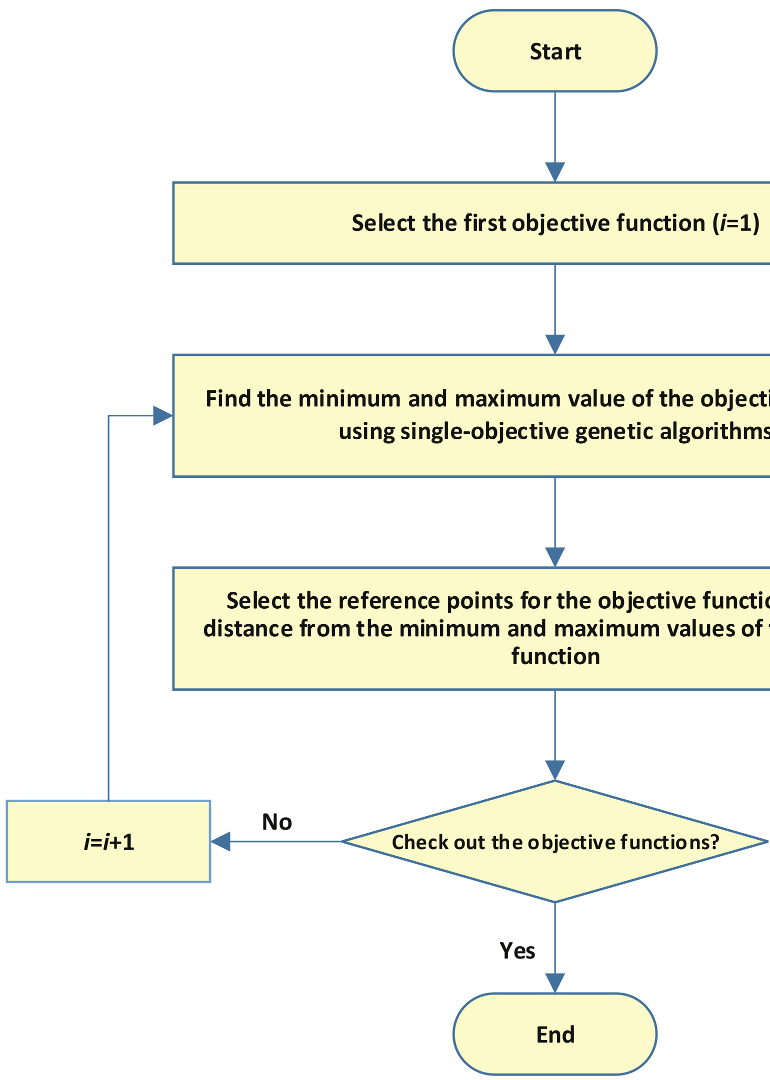


Fig. 3. Algorithm used to determine the reference points in the solution space.

Table 6
Scale of small and large size problems.

Features	Number in the small size problems	Number in the large size problems
Central Warehouses	2	4
Hospitals	10	20
1st Echelon Vehicles	4	8
Affected Areas (Demand Points)	30	60
2nd Echelon Vehicles	12	24
Product Types	3	6

5.3. Handling the constraints of the model

The constraints of the model are handled as penalties of a meta-heuristic algorithm. That is, the constraints are added as penalty functions to the objective function. Doing so, the constrained optimization problem is turned into an unconstrained optimization problem. More precisely, if the individuals of a population (i.e., the feasible solutions of the problem) violate the related constraints, a penalty is added to the objective function that increases abnormally; if not, no penalty is added to the objective function (the penalty value is zero).

6. Computational results

An attempt to solve the proposed model was made using three methods: the Epsilon-Constraint method, NSGA-II and RPBNSGA-II. The obtained results were examined using ANOVA.

To solve the model and obtain the Pareto front of the solutions, the Epsilon-Constraint exact algorithm was implemented in Lingo 14. Due to the high complexity of the problem deriving from the presence of several zero/one decision variables and numerous constraint bunches interlinked to one another, this algorithm was not able to solve the problem. Therefore, the problem was coded and solved by running NSGA-II and RPBNSGA-II in MATLAB.

The NSGA-II and RPBNSGA-II algorithms were run for several instances of small and large problems: 30 small size problems and 30 large size problems were simulated and each one of them was solved by both NSGA-II and RPBNSGA-II. Table 6 shows the scale of small and large problems used for the simulations. It is important to state that the simulated data and parameters of the 60 problems were generated randomly.

Regarding the technical specifications, the test problems were carried out using a standard desktop computer with Intel(R) Core(TM) i7-4790 CPU @ 3.60 GHz and 16.0 GB RAM.

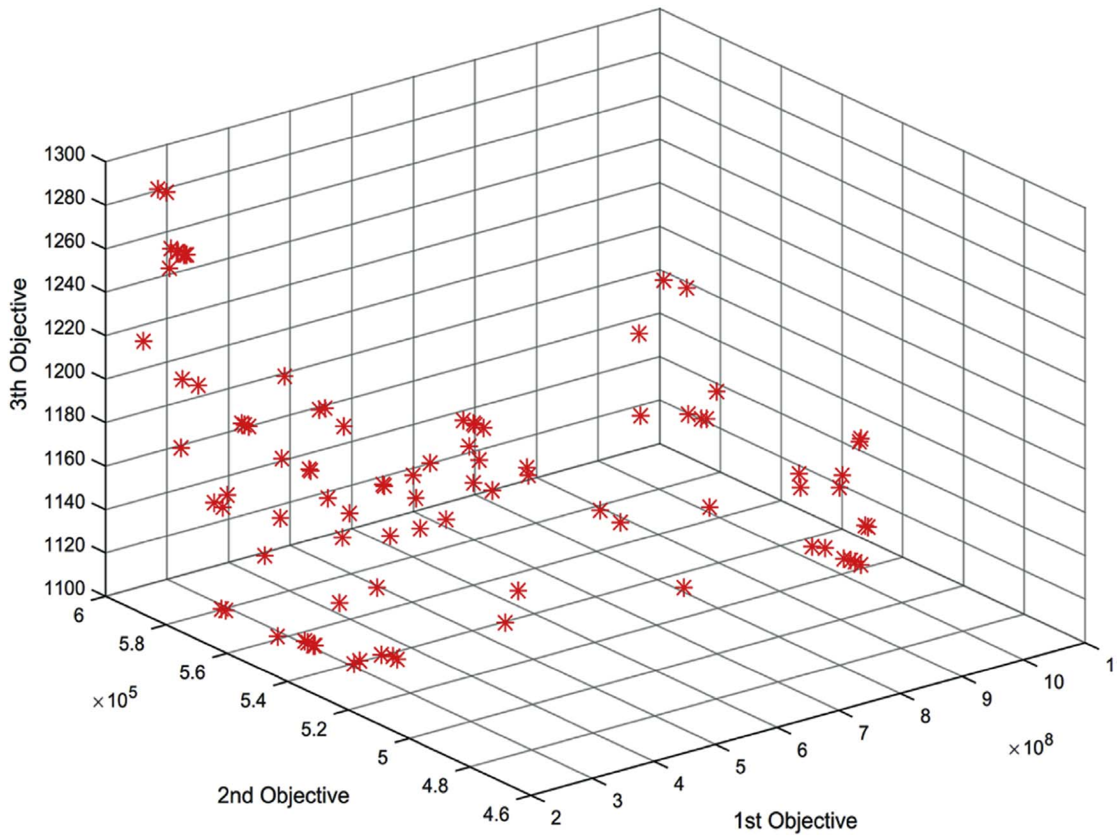


Fig. 4. Pareto solutions obtained through NSGA-II for the last small size problem in a three-dimensional space.

6.1. Analyzing the results of small size problems

As mentioned above, 30 small size problems were solved implementing NSGA-II and RPBNSGA-II. Figs. 4 and 5 provide a three-dimensional representation of the Pareto solutions to the last small size problem obtained through NSGA-II and RPBNSGA-II, respectively. We used ANOVA to calculate and compare the averages of the quality indices of the Pareto solutions in the two methods. Hence, we compared the solutions obtained applying these two methods by means of the statistical software Minitab 16.

After one-way ANOVA and the Tukey Test, the average value of the numbers of non-dominated solutions (NSs) using NSGA-II equals 91.2667 while it is equal to 83.7667 when using RPBNSGA-II. Since the greater is this average, the higher is the quality of the solutions, we can state that NSGA-II performs better than RPBNSGA-II in terms of number of NSs when solving small size problems.

Regarding the output of one-way ANOVA for the running time of the algorithms, the P-value observed using Minitab 16 is zero. Since the P-value is less than 0.05, H0 is rejected and it can be concluded that the average running time values of the two algorithms, NSGA-II and RPBNSGA-II, are not equal and there is a significant difference between them.

This claim can also be derived from the output of the Tukey Test. According to the grouping table of the Tukey Test, the RPBNSGA-II code is to be placed in group A while the NSGA-II code belongs to group B. Consequently, since the codes are not in the same group, the averages of the running time values of the two algorithms differ. The significance of this difference is also confirmed by the confidence interval produced by the Tukey Test. This interval measures the differences between the mean of the CPU(sec.) performance values in NSGA-II and the corresponding one in RPBNSGA-II and does not comprise 0.

The mean of the CPU(sec.) performance values equals 64.2694 in NSGA-II and 64.8433 in RPBNSGA-II. Since a smaller value for this index means a higher quality for the solutions, it can be concluded that NSGA-II performs better than RPBNSGA-II in terms of running time values when solving small size problems.

6.2. Analyzing the results of large size problems

As mentioned earlier, 30 large size problems were solved implementing NSGA-II and RPBNSGA-II. Figs. 6 and 7 provide a three-dimensional representation of the Pareto solutions to the last large size problem obtained through NSGA-II and RPBNSGA-II, respectively.

After one-way ANOVA and the Tukey Test, the average value of the numbers of NSs using NSGA-II equals 72. 9333 while it is equal to 79.8 when using RPBNSGA-II. Since, again, the greater is this average value, the higher is the quality of the solutions, we can state that RPBNSGA-II performs better than NSGA-II relatively to the number of NSs when solving large size problems.

According to the output of one-way ANOVA for the running time of the algorithms, the P-value observed using Minitab 16 is 0.004. Since the P-value is less than 0.05, H0 is rejected and it can be concluded that the average running time values of the two algorithms, NSGA-II and RPBNSGA-II, are not equal but there is a significant difference among them.

This claim can also be derived from the Tukey Test outputs. According to the grouping table of the Tukey Test, the NSGA-II code is to be placed in group A while the RPBNSGA-II code belongs to group B. Consequently, since the codes are not in the same group, the averages of the running time values of the two algorithms differ. The significance of this difference is also confirmed by the confidence interval produced by the Tukey Test. This interval measures the differences between the mean of the CPU(sec.) performance values in NSGA-II and that in RPBNSGA-II and does not comprise 0.

The mean of the CPU(sec.) performance values equals 98.1754 in NSGA-II and 82.0839 in RPBNSGA-II. Since a smaller value for this

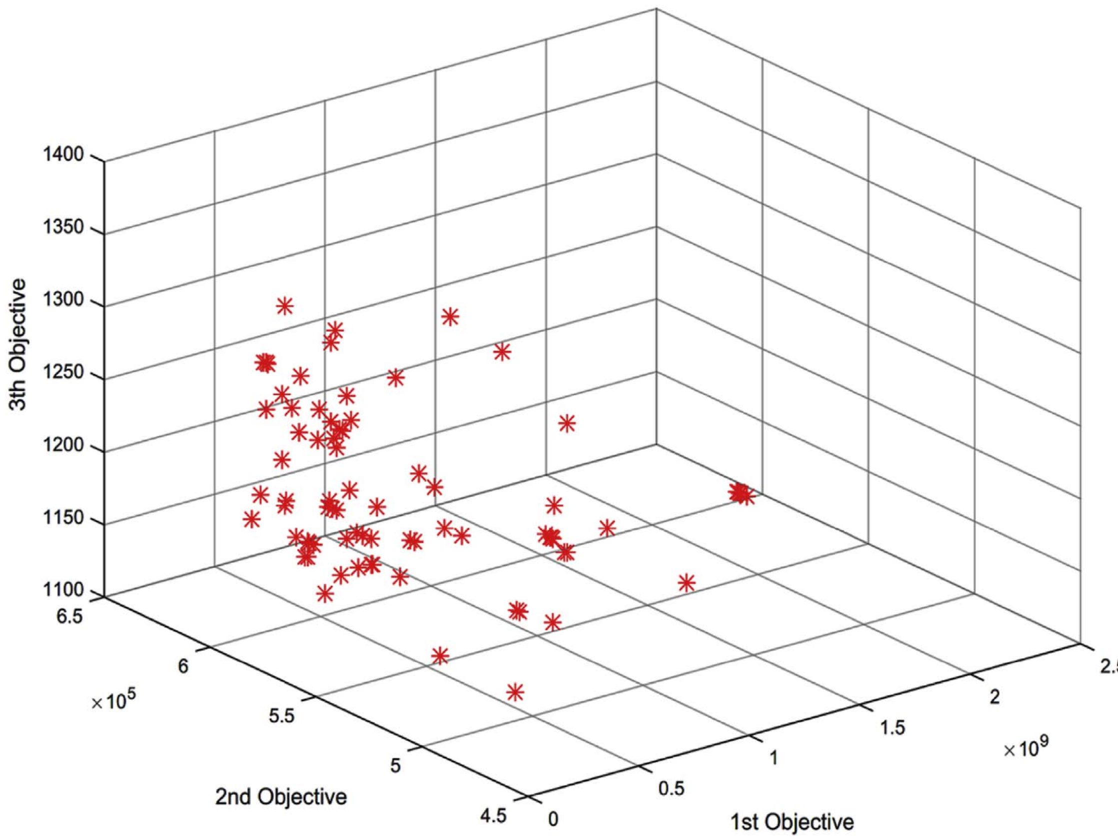


Fig. 5. Pareto solutions obtained through RPBNSGA-II for the last small size problem in a three-dimensional space.

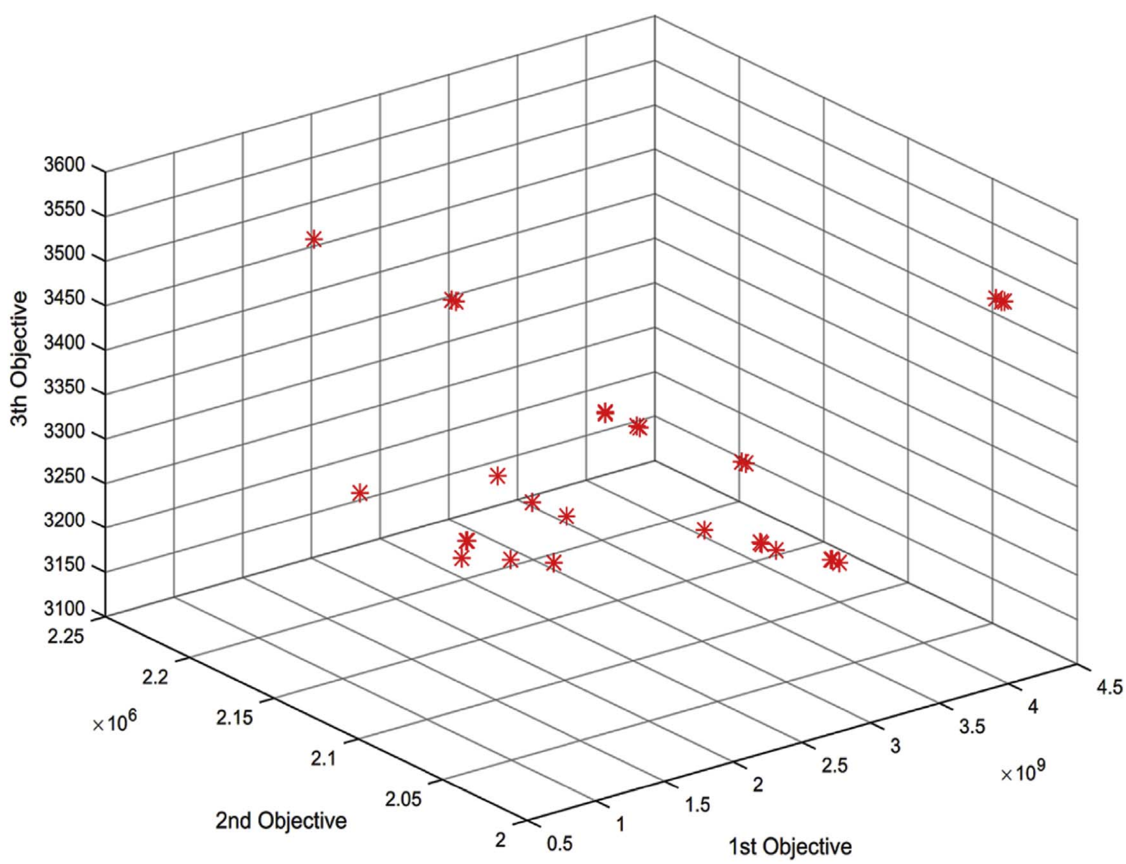


Fig. 6. Pareto solutions obtained through NSGA-II for the last large size problem in a three-dimensional space.

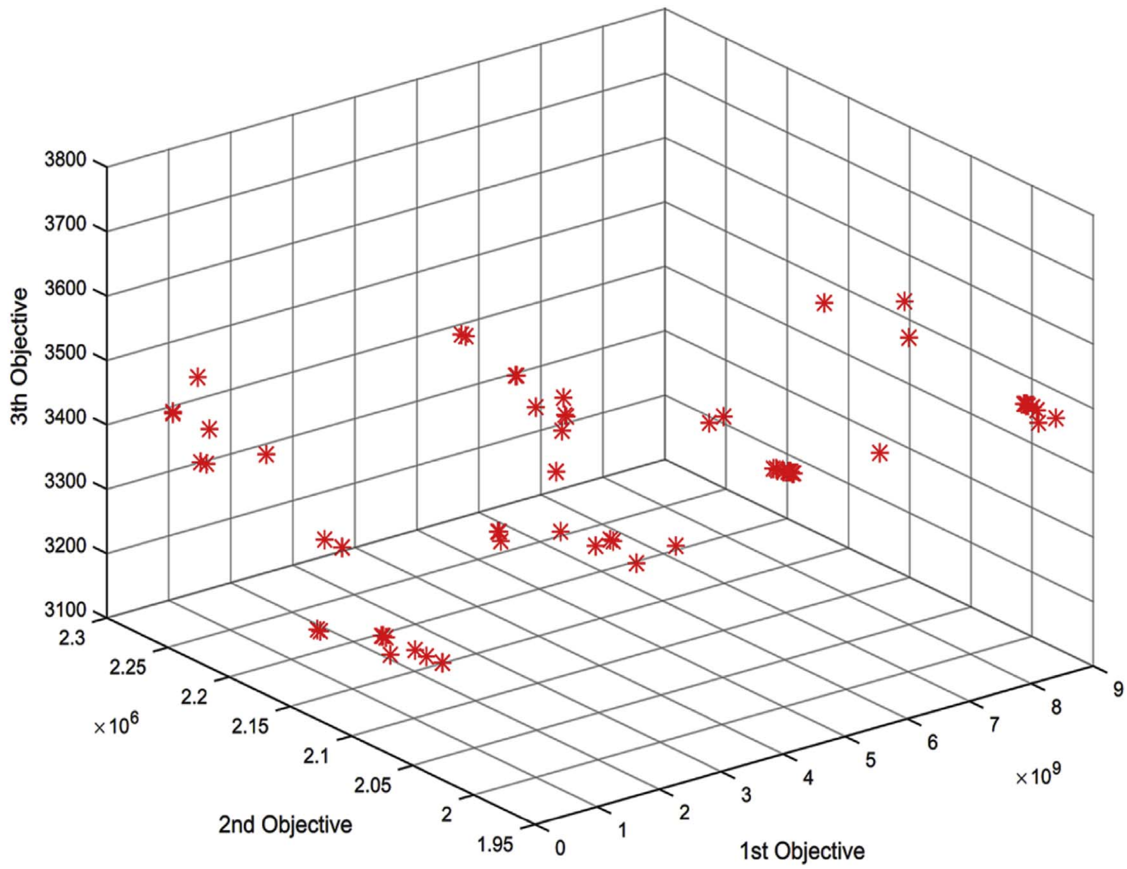


Fig. 7. Pareto solutions obtained through RPBNSGA-II for the last large size problem in a three-dimensional space.

index means a higher quality for the solutions, it can be stated that RPBNSGA-II performs better than NSGA-II in terms of running time values when solving large size problems.

Overall, based on ANOVA, it can be concluded that NSGA-II outperforms RPBNSGA-II with respect to both the number of NSs criterion and the CPU time criterion in small size problems. On the other hand, RPBNSGA-II shows to perform better than NSGA-II with respect to both criteria in large size problems.

7. Conclusion

Natural disasters such as earthquakes, floods, hurricanes, and Tsunamis, continue to impose substantial life and financial losses. Despite the recent scientific and technological achievements, human beings are not yet able to forecast these dramatic events. In this regard, many studies have been performed focusing on pre-disaster planning to prevent or reduce the effects of these events as well as on post-disaster planning to take relief actions.

After examining the previous studies, the corresponding models and suggestions for future research, we have identified a gap existing in the attempts to simultaneously obtain an optimal pre-positioning of the warehouses and minimize the costs of warehousing and relief products transportation. Filling in this gap is even more important when relief products also include perishable ones.

This study has presented a mixed integer linear programming (MILP) model to design a new humanitarian logistic network. The aim of this research has been to propose a novel multi-echelon logistic network with central warehouses location finding and inventory planning and controlling in the pre-disaster phase as well as relief transportation vehicle routing to provide the damaged areas with the necessary products in the post-disaster phase.

The proposed network has been modelled through three objective functions. The first objective function minimizes the total cost of procurement and preparation in the pre-disaster phase. This cost derives from the creation of warehouses, warehousing, transporting relief products from suppliers to warehouses, and managing an inventory control of perishable products. The second objective function minimizes the total cost of relief operations in the post-disaster phase, this cost including costs of transportation, product loading and unloading, product shortages and unused products. Finally, the third objective function minimizes the total operational relief time in the action phase after the disaster has occurred. This time includes transportation, loading and unloading time.

In particular, three transportation stages have been considered: from suppliers to central warehouses, from central warehouses to hospitals and from hospitals to damaged areas.

The associated transportation problem has been modelled as a multi-echelon multiple depots vehicle routing problem (MEMDVRP). The optimal inventory of relief products has been planned and controlled through the optimal locations of the central warehouses. Finally, all the relief products in the model have been assumed perishable. Thus, the model has also accounted for the need of restoring them after the expiration date.

The proposed model has been solved using the Epsilon-Constraint method, NSGA-II, and RPBNSGA-II. Due to the high complexity of the problem, the Epsilon-Constraint method, coded using the Lingo software, was unable to produce a solution to the problem. Therefore, the problem was coded and solved in NSGA-II and RPBNSGA-II. The results and the information obtained from the analysis of variance (ANOVA) were examined using the Minitab software.

On the basis of the results obtained, we have concluded that NSGA-II performs better than RPBNSGA-II in small size problems. At the same time, RPBNSGA-II outperforms NSGA-II in large size problems.

Finally, we would like to conclude presenting some suggestions for a further development of this study. Extensions of the proposed model could focus on the following points.

a. Prioritizing the relief products and considering these priorities when planning the transportation of the products to hospitals and damaged areas.
b. Considering the conveyance of the injured people from damaged areas to hospitals and relief centers.
c. Considering other transportation models such as air transportation (helicopter and plane) to help the injured people.
d. Considering uncertainties relative to the demand and available routes.

Acknowledgement

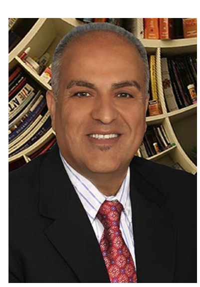
The authors would like to thank the anonymous reviewers and the editor for their insightful comments and suggestions.

Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.seps.2017.12.004.

References

[1] Barzinpour F, Esmaeili V. A multi-objective relief chain location distribution model for urban disaster management. Int J Adv Manuf Technol 2014;70(5–8):1291–302.
[2] Guha-Sapir D, Vos F, Below R, Ponserre S. Annual disaster statistical review 2011: the numbers and trends. Brussels: Centre for Research on the Epidemiology of Disasters (CRED); 2012.
[3] Holguín-Veras J, Jaller M, Van Wassenhove LN, Pérez N, Wachtendorf T. On the unique features of post-disaster humanitarian logistics. J Oper Manag 2012;30(7):494–506.
[4] Sprenger R, Mönch L. A methodology to solve large-scale cooperative transportation planning problems. Eur J Oper Res 2012;223(3):626–36.
[5] Özdamar L, Ertem MA. Models, solutions and enabling technologies in humanitarian logistics. Eur J Oper Res 2015;244(1):55–65.
[6] Baharmand H, Comes T, Lauras M. Managing in-country transportation risks in humanitarian supply chains by logistics service providers: insights from the 2015 Nepal earthquake. Int J DisastRisk Reduct 2017;24:549–59.
[7] Guha-Sapir D, Hoyois P, Below R. Annual disaster statistical review 2015: the numbers and trends. Brussels: Centre for Research on the Epidemiology of Disasters (CRED); 2016.
[8] Li X, Batta R, Kwon C. Effective and equitable supply of gasoline to impacted areas in the aftermath of a natural disaster. Soc Econ Plann Sci 2017;57:25–34.
[9] Ahmadi M, Seifi A, Tootooni B. A humanitarian logistics model for disaster relief operation considering network failure and standard relief time: a case study on San Francisco district. Transport Res E Logist Transport Rev 2015;75:145–63.
[10] Luis E, Dolinskaya IS, Smilowitz KR. Disaster relief routing: integrating research and practice. Soc Econ Plann Sci 2012;46(1):88–97.
[11] Perboli G, Tadei R, Vigo D. The two-echelon capacitated vehicle routing problem: models and math-based heuristics. Transport Sci 2011;45(3):364–80.
[12] Baskaya S, Ertem MA, Duran S. Pre-positioning of relief items in humanitarian logistics considering lateral transhipment opportunities. Soc Econ Plann Sci 2017;57:50–60.
[13] Goli A, Alinaghian M. Location and multi-depot vehicle routing for emergency vehicles using tour coverage and random sampling. Decision Sci Lett 2015;4(4):579–92.
[14] Sahebi IG, Arab A, Moghadam MR Sadeghi. Analyzing the barriers to humanitarian supply chain management: a case study of the Tehran Red Crescent Societies. Int J Disast Risk Reduct 2017;24:232–41.
[15] Najafi M, Eshghi K, de Leeuw S. A dynamic dispatching and routing model to plan/re-plan logistics activities in response to an earthquake. OR spectrum 2014;36(2):323–56.
[16] Rezaei-Malek M, Tavakkoli-Moghaddam R. Robust humanitarian relief logistics network planning. Uncertain Supply Chain Manag 2014;2(2):73–96.
[17] Rath S, Gutjahr WJ. A math-heuristic for the warehouse location–routing problem in disaster relief. Comput Oper Res 2014;42:25–39.
[18] Garrido RA, Lamas P, Pino FJ. A stochastic programming approach for floods emergency logistics. Transport Res E Logist Transport Rev 2015;75:18–31.
[19] Zhang Y, Qi M, Lin WH, Miao L. A metaheuristic approach to the reliable location routing problem under disruptions. Transport Res E Logist Transport Rev 2015;83:90–110.
[20] Onan K, Ülengin F, Sennaroğlu B. An evolutionary multi-objective optimization approach to disaster waste management: a case study of Istanbul, Turkey. Expert Syst Appl 2015;42(22):8850–7.
[21] Bastian ND, Griffin PM, Spero E, Fulton LV. Multi-criteria logistics modeling for military humanitarian assistance and disaster relief aerial delivery operations. Optic Lett 2016;10(5):921–53.
[22] Alem D, Clark A, Moreno A. Stochastic network models for logistics planning in disaster relief. Eur J Oper Res 2016;255(1):187–206.
[23] Celik E, Aydin N, Gumus AT. A stochastic location and allocation model for critical items to response large-scale emergencies: a case of Turkey. An Int J Optim Control Theor Appl (IJOCTA) 2016;7(1):1–15.
[24] Tofighi S, Torabi SA, Mansouri SA. Humanitarian logistics network design under mixed uncertainty. Eur J Oper Res 2016;250(1):239–50.
[25] Zhu C, Fang G, Wang Q. Optimization on emergency resources transportation network based on bayes risk function: a case study. Math Probl Eng 2016;2016.
[26] Bai X. Optimal decisions for prepositioning emergency supplies problem with Type-2 fuzzy variables. Discrete Dynam Nat Soc 2016:9275192http://dx.doi.org/10.1155/2016/9275192. 17 pages.
[27] Fereiduni M, Hamzehee M. A P-robust model in humanitarian logistics in a non-neutral political environment. Uncertain Supply Chain Manag 2016;4(4):249–62.
[28] Tavana M, Li Z, Mobin M, Komaki M, Teymourian E. Multi-objective control chart design optimization using NSGA-III and MOPSO enhanced with DEA and TOPSIS. Expert Syst Appl 2016;50:17–39.
[29] Piasson D, Bíscaro AA, Leão FB, Mantovani RS. A new approach for reliability-centered maintenance programs in electric power distribution systems based on a multiobjective genetic algorithm. Elec Power Syst Res 2016;137:41–50.
[30] Mousavi SM, Sadeghi J, Niaki STA, Tavana M. A bi-objective inventory optimization model under inflation and discount using tuned Pareto-based algorithms: NSGA-II, NRGA, and MOPSO. Appl Soft Comput 2016;43:57–72.
[31] Rezaei-Malek M, Tavakkoli-Moghaddam R, Cheikhrouhou N, Taheri-Moghaddam A. An approximation approach to a trade-off among efficiency, efficacy, and balance for relief pre-positioning in disaster management. Transport Res E Logist Transport Rev 2016;93:485–509.
[32] Rezaei-Malek M, Tavakkoli-Moghaddam R, Zahiri B, Bozorgi-Amiri A. An interactive approach for designing a robust disaster relief logistics network with perishable commodities. Comput Ind Eng 2016;94:201–15.
[33] Fereiduni M, Shahanaghi K. A robust optimization model for distribution and evacuation in the disaster response phase. J Ind Eng Int 2017;13(1):117–41.
[34] Goldschmidt KH, Kumar S. Humanitarian operations and crisis/disaster management: a retrospective review of the literature and framework for development. Int J DisastRisk Reduct 2016;20:1–13.
[35] Zheng YJ, Chen SY, Ling HF. Evolutionary optimization for disaster relief operations: a survey. Appl Soft Comput 2015;27:553–66.
[36] Seada H, Deb K. U-NSGA-III: a unified evolutionary optimization procedure for single, multiple, and many objectives: proof-of-principle results. Gaspar-Cunha A, Henggeler Antunes C, Coello C, editors. Evolutionary multi-criterion optimization. EMO 2015. Lecture notes in computer science, vol. 9019. Cham: Springer; 2015. p. 34–49.
[37] Vahdani B, Veysmoradi D, Shekari N, Mousavi SM. Multi-objective, multi-period location-routing model to distribute relief after earthquake by considering emergency roadway repair. Neural Comput Appl 2016. http://dx.doi.org/10.1007/s00521-016-2696-7.
[38] Boonmee C, Arimura M, Asada T. Facility location optimization model for emergency humanitarian logistics. Int J DisastRisk Reduct 2017;24:485–98.
[39] Swamy R, Kang JE, Batta R, Chung Y. Hurricane evacuation planning using public transportation. Soc Econ Plann Sci 2017;59:43–55.
[40] Vahdani B, Veysmoradi D, Noori F, Mansour F. Two-stage multi-objective location-routing-inventory model for humanitarian logistics network design under uncertainty. Int J DisastRisk Reduct 2017. http://dx.doi.org/10.1016/j.ijdrr.2017.10.015.
[41] Nair DJ, Grzybowska H, Fu Y, Dixit VV. Scheduling and routing models for food rescue and delivery operations. Soc Econ Plann Sci 2017. http://dx.doi.org/10.1016/j.seps.2017.06.003.
[42] Noham R, Tzur M. Designing humanitarian supply chains by incorporating actual post-disaster decisions. Eur J Oper Res 2018;265(3):1064–77.
[43] Mitsotakis A, Kassaras G. Managing disaster in the Ionian Sea: planning and optimizing logistics for disaster relief operations for the Island of Kefalonia. DTIC Document; 2010.



Madjid Tavana is Professor and Distinguished Chair of Business Analytics at La Salle University, where he serves as Chairman of the Business Systems and Analytics Department. He also holds an Honorary Professorship in Business Information Systems at the University of Paderborn in Germany. Dr. Tavana is Distinguished Research Fellow at the Kennedy Space Center, the Johnson Space Center, the Naval Research Laboratory at Stennis Space Center, and the Air Force Research Laboratory. He was recently honored with the prestigious Space Act Award by NASA. He holds an MBA, PMIS, and PhD in Management Information Systems and received his Post-Doctoral Diploma in Strategic Information Systems from the Wharton School at the University of Pennsylvania. He has published 12 books and over 250 research papers in international scholarly academic journals. He is the Editor-in-Chief of *Decision Analytics*, *International Journal of Applied Decision Sciences, International Journal of Management and Decision Making, International Journal of Knowledge Engineering and Data Mining, International Journal of Strategic Decision Sciences,* and *International Journal of Enterprise Information Systems.*

Amir-Reza Abtahi is Assistant Professor and chair of Information Technology Management department at Kharazmi University in Tehran, Iran. He received his MSc and PhD in Operations and Production Management from ATU, Tehran, Iran. He has published several papers in international journals such as Expert Systems with Applications, Reliability Engineering & System Safety, Annals of Operations Research, Optimization Methods and Software, Journal of Mathematical Modelling and Algorithms in Operations Research, and Journal of Industrial Engineering International. His research interest includes applied operations research, applied computational intelligence, and operations management.

Debora Di Caprio is Visiting Research Fellow at the Department of Mathematics and Statistics of York University (Canada), researcher in the INTBM International Business and Markets Group at the Universidad Complutense de Madrid (Spain) and tenured instructor of Mathematics at the Polo Tecnologico IISS "G. Galilei" of Bolzano (Italy). She holds a MS and PhD in Pure Mathematics from York University (Canada) and has been researcher and contract professor in Italy at the Seconda Università di Napoli, the Free University of Bolzano and the Università di Trento. She has over 80 papers in international journals on mathematics, operational research, and decision theory.

Reza Hashemi received his MSc degree in industrial management from School of Management at Kharazmi University and BSc degree in Railway transportation engineering from School of Railway Engineering at the University of Science and Technology in Iran. His research interests are in project management, metaheuristic algorithms, multi-criteria decision making, mathematical optimization, system analysis, and simulation of queuing systems.

Reza Yousefi-Zenouz is an assistant professor of operations and information management at kharazmi University. He received his PhD in Operations Research from University of Tehran and MS degree in Operations management in from Shahid Beheshti University in Iran. His research interests are in supply chain management, multi-criteria decision making, machine learning and operations research. He has published several papers in peer reviewed journals and conferences.