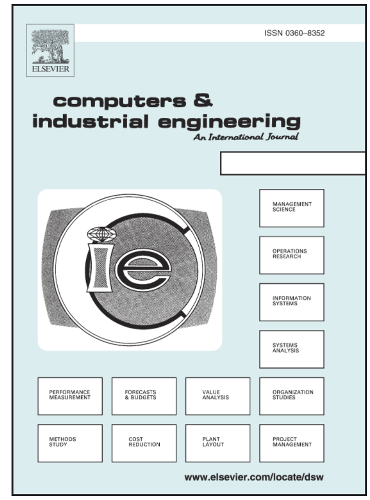
Rezaei, Mahdieh, Afsahi, Mohsen, Shafiee, Mahmood and Patriksson, Michael
(2020) ***A bi-objective optimization framework for designing an efficient fuel supply chain network in post-earthquakes.*** **Computers & Industrial Engineering, 147 . ISSN 0360-8352.**

Journal Pre-proofs



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PII: S0360-8352(20)30388-0
DOI: https://doi.org/10.1016/j.cie.2020.106654
Reference: CAIE 106654

To appear in: *Computers & Industrial Engineering*

Received Date: 8 October 2019
Revised Date: 4 May 2020
Accepted Date: 6 July 2020

Please cite this article as: Rezaei, M., Afsahi, M., Shafiee, M., Patriksson, M., A bi-objective optimization framework for operating an efficient fuel supply chain network in post-earthquakes, *Computers & Industrial Engineering* (2020), doi: https://doi.org/10.1016/j.cie.2020.106654

A bi-objective optimization framework for operating an efficient fuel supply chain network in post-earthquakes

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A bi-objective optimization framework for operating an efficient fuel supply chain network in post-earthquakes

Abstract

Earthquakes are the most sudden and unpredictable natural disaster which can cause serious damages in terms of deaths, injuries, and property loss. When an earthquake occurs, it is very important to respond immediately to peoples' emergency needs through proper distribution of critical resources such as medical care, water, food, shelters, etc. Fuel is also one of the most critical needs which must be provided without delay to the population affected by the earthquake, especially the vulnerable children and elderly people. This paper develops a nonlinear bi-objective optimization framework for operating an efficient and effective fuel supply chain network in earthquake-hit areas. The objective functions include minimizing the penalties due to unsatisfied and/or lost fuel demands and minimizing the difference between the satisfied demands in different damaged areas. Some assumptions and constraints, such as the existence of multiple central depots, limited vehicle capacities, time available to respond to the incident, are also considered in the modeling. Two multi-objective evolutionary algorithms (MOEAs), including a non-dominated sorting genetic algorithm (NSGA-II) and a multi-objective particle swarm optimization (MOPSO), are proposed to solve the optimization problem. Since the performance of these algorithms is significantly dependent on their parameters, a Taguchi method is used to tune the algorithms' parameters. In addition, four performance metrics are defined to evaluate and compare the performance of the algorithms. A hypothetical earthquake with actual dimensions and realistic data in Yazd province of Iran is presented as a case study, and finally, helpful managerial insights are provided through conducting a sensitivity analysis.

Keywords

Disaster management; earthquake; bi-objective optimization; fuel supply chain; non-dominated sorting genetic algorithm (NSGA-II); multi-objective particle swarm optimization (MOPSO).

1. Introduction

The number of casualties and the size of damage resulting from natural hazards have increased continuously over the last decades. For example, during the first decade of the 21st century, the natural disasters such as flood, fire, earthquake, tornado and windstorm have affected over 3.65 million people [1]. Among the natural disasters, earthquakes are the leading causes of death, injury and disability in the world [2]. Earthquakes may also cause man-made hazards such as fires, dam failures and toxic material spills. According to the U.S. Geological Survey [3], more than 1,000 earthquakes occurred in 70 countries during the last century. These earthquakes were in total responsible for about 2 million deaths. Among all the countries, China, Indonesia, Iran, Turkey, Japan, Philippines, India and Pakistan are recognized as the most vulnerable countries to earthquakes.

After an earthquake occurs, it is critical to quickly respond to emergency needs of people who have been affected. During the response phase, transportation of injured people to emergency tents and hospitals as well as distribution of vital commodities and materials (such as food, medicine, fuel, provisions for sanitation, shelters, and water) are vital. An effective planning of these activities in an earthquake situation can decrease the loss of lives and minimize the aforementioned negative effects. Over the past years, many researchers have recognized the importance of this subject. For instance, Fiedrich *et al.* [4], Jotshi *et al.* [5] and Jin *et al*. [6] focused on the transportation of injured people to emergency treatment facilities. Other researchers like Najafi *et al.* [2], Yi and Kumar [7], Yi and Özdamar [8], Özdamar [9], Özdamar and Demir [10], and

Fereiduni and Shahanaghi [11] have addressed the logistics of disaster relief commodities as well as transport of injured people during the earthquake response phase.

As the literature review shows, most of the previous studies have focused on the distribution of vital commodities and materials during an earthquake. Fuel is also one of the most important commodities which must be provided without delay to the population affected by the earthquake, especially the most vulnerable groups. The damage caused by an earthquake to fuel distribution systems can be extremely costly. For this reason, the sites and fuel networks must be designed and installed according to ruling standards so as to ensure they are completely safe and are able to protect the citizens when confronted with unexpected crises. The fuel is needed to provide heat and light to people and if it does not reach people on time, an increased death rate will be inevitable. Thus, fuel consumption rate may grow substantially in earthquake-hit areas in a short period of time after the disaster. Therefore, it is necessary to operate an efficient and effective supply chain network for distribution of fuel during an earthquake.

To the best of the authors' knowledge, there is no research addressing the optimal operation of fuel distribution network after an earthquake event. The distribution and supply of fuel to earthquake-affected areas is subject to larger number of constraints than distribution of other commodities. An example of such constraints is the limited time available to deliver fuel to people, or the type of vehicles needed to use for transportation of fuel. A brief review of the literature shows that several researchers have studied the optimal distribution of other commodities such as medical care, water, food, shelter, etc. In what follows, a brief review of these studies is provided:

The early researches concerning the response to disaster were undertaken by Knott [12, 13], where linear programming (LP) models are proposed to optimize the schedules of vehicles transporting the bulk food to disastrous areas. These studies only considered the distribution of food; however, in addition to food, the distribution of other resources is also necessary. Haghani and Oh [14] proposed a bi-objective model for transporting diverse commodities such as clothing, food, drugs, medical supplies, machinery and human resources. The objective function included minimizing the loss of lives and maximizing the output of rescue operations. Barbarosoğlu *et al.* [15] developed a mathematical model to solve a decision-making problem corresponding to the operational and tactical timing of helicopters used for rescue operations in disaster-hit areas. Barbarosoğlu and Arda [16] formulated a two-stage stochastic model for planning the distribution of emergency medical commodities in areas affected by an earthquake. Özdamar *et al.* [17] developed a logistics planning model to optimize the transportation of commodities such as medical materials and personnel, rescue equipment and teams as well as fresh food to distribution centers in earthquake-affected areas. Meanwhile, Tzeng *et al*. [18] designed an optimal relief delivery system by developing a multi-objective programming approach. In this model, the total cost and travel times are minimized while maximizing the satisfaction during the planning horizon.

Kondaveti and Ganz [19] determined an optimal resource deployment and dispatching strategy in natural disasters through the use of a decision support tool called DIORAMA which was built based on rapid information collection and accurate resource tracking functionalities. Mete and Zabinsky [20] presented a stochastic programming method for storing and dispensing of medical devices during a natural disaster. In another study, Sheu [21] proposed a dynamic model for relief-demand forecasting in emergency logistics operations under natural disasters. The model first used a data fusion method to predict the relief demand in affected areas, then it clustered the areas by means of a fuzzy clustering method, and finally it ranked the order of priority of groups using a multi-criteria decision making (MCDM) approach. Lin *et al.* [22] formulated a multi-objective integer programming model for logistic planning of critical items during a disaster's response phase. The model considered multiple items, multiple vehicles, multiple planning periods, a flexible time window and a split delivery strategy scenario into account. The model included two objective functions which minimized the total unsatisfied demand while it also minimized the total travelling time. Nolz *et al.* [23] presented a multi-objective optimization framework to facilitate the dispatch of relief aid in a post-disaster situation, such that the total travel time was minimized and the number of requests covered by the logistics system was maximized. Afshar and Haghani [24] developed a model to facilitate the logistics operations in natural disaster-affected areas. They proposed a single-objective optimization problem to schedule the flow of relief commodities with the aim of minimizing the amount of unsatisfied demands in the supply chain network. Berkoune *et al.* [25] formulated a mathematical model to minimize the total travel time as well as the number of transport vehicles required for the transportation of humanitarian aid in emergency situations. Suzuki [26] empirically examined the negative impact of shortage in fuel supply on achieving the logistical goals and compared with the cases where there is a shortage in other emergency supplies during a disaster. Moreover, the study investigates what types of vehicles are affordable when the fuel supply is limited. Zhang *et al.* [27] developed an integer optimization model to assign the available resources to demand points where there exist some constraints on the resources. For solving the model, the authors proposed a heuristic algorithm based on LP and network optimization. Barzinpour and Esmaeili [28] optimized the planning phase of disaster management by a multi-objective mixed-integer LP model. The model includes two objective functions to be optimized simultaneously (one is concerned with the total cost and another is concerned with the coverage provided by logistics system). Ahmadi *et al.* [29] presented a two-stage stochastic programming model to solve a multi-depot location-routing problem in an earthquake response phase. Huang *et al.* [30] presented a multi-objective optimization model with three objective functions, including lifesaving effectiveness, delay cost, and fairness, in order to determine the resource allocation distribution in emergency situations. Rezaei-Malek *et al* [31] designed a disaster-relief logistics system to determine the optimal location-allocation and the distribution plan in an integrated manner. Furthermore, they determined the ordering policy to supply the perishable commodities before a disaster occurs.

Tofighi *et al.* [32] studied a two-echelon humanitarian relief logistics network design problem involving multiple 'central warehouses' and 'local distribution centers'. They developed a two-stage scenario-based possibilistic-stochastic programming model to solve the main logistical problems in the pre- and post-earthquake phases. Zokaee *et al.* [33] studied a three-level humanitarian relief network design problem involving multiple suppliers, relief distribution centers, and affected areas. They proposed a bi-objective optimization model to minimize the total costs of the relief chain as well as maximizing the satisfaction level of people in the affected areas. Fahimnia *et al*. [34] proposed a stochastic programming model to minimize the total cost and delivery time for a blood supply chain network under disaster conditions. Mohamadi and Yaghoubi [35] formulated a bi-objective stochastic model to optimize the location of distribution points as well as medical supply centers. Cao *et al.* [36] presented a mixed-integer nonlinear optimization model to maximize the satisfaction of affected people in an earthquake as well as minimizing the deviation of people's satisfaction levels. Samani *et al*. [37] proposed a multi-objective mixed-integer linear programming model to design a reliable blood supply chain system in disastrous situations. The objective functions considered in the study include: total cost, number of unsatisfied demand, and delivery time of blood products to demand zones. Nikoo *et al.* [38] proposed a multi-objective optimization framework to design a network for accomplishing emergency response travels during an earthquake event such that the length, time and number of paths were minimized.

Table 1 summarizes the above-reviewed literature and categorizes the papers according to their objective function(s) and model assumptions.

Table 1

Table 1. A summary of the studies about relief response in an earthquake.

Because of the great importance of fuel distribution in the post-earthquake management, this paper addresses the optimization of fuel supply chain network in earthquake-hit areas. The fuel distribution system consists of two main components, including energy distribution centers and earthquake-affected areas to where the fuel is distributed. The problem is formulated as a nonlinear bi-objective mathematical model in which the unsatisfied and lost demands in an emergency situation are expressed in terms of a penalty function. The two objective functions include (*i*) minimizing the delay penalties (due to unsatisfied and lost demand) and (*ii*) minimizing the difference between the satisfied demands in different areas. Some assumptions and constraints, such as the existence of multiple central depots, limited vehicle capacities, time available to respond to the incident, etc. are also considered in the modeling. Two multi-objective evolutionary algorithms (MOEAs), including a non-dominated sorting genetic algorithm (NSGA-II) and a multi-objective particle swarm optimization (MOPSO), are proposed to solve the optimization problem. Since the parameters of these algorithms have considerable impact on their performance, a Taguchi model is utilized to tune the algorithms' parameters. In addition, four performance metrics are defined to evaluate and compare the performance of the algorithms. A hypothetical earthquake with actual dimensions and realistic data in Yazd city in Iran is presented and the Pareto optimal front solutions are obtained by using the weighted sum method (WSM). Finally, helpful managerial insights will be provided by conducting a sensitivity analysis.

The reminder of this paper is structured as follows. The problem is stated and the model assumptions are defined in Section 2. The mathematical formulation of the problem is presented in Section 3. Section 4 proposes two solution approaches to the problem. Section 5 presents a numerical study, and finally, conclusions and future work are discussed in Section 6.

2. Problem statement

Since earthquakes are unpredictable and occur without warning, it is critical for countries to provide services that are essential to people's lives after earthquake. This paper aims to propose an optimization framework for operating an efficient and effective fuel supply chain network in post-earthquake situations. The elements of the fuel supply chain network are illustrated in Figure 1. As can be seen, the fuel supply chain network is comprised of a distribution center at the left-hand side, temporary warehouses and transport vehicles in the middle, and the earthquake-affected points at the right-hand side of the network. The distribution center itself contains relief commodities with some inventory. The temporary warehousing centers include relief centers which are smaller than distribution centers and are in close proximity to the affected areas. Vehicles have limited capacity but each vehicle can travel to multiple affected points. The affected points are prioritized according to the number of their emergency places for fueling such as hospitals.

Figure 1

Figure 1. A fuel supply chain network in post-earthquake situations.

In this study, several assumptions are made. First assumption is related to the transport vehicles. They are considered homogeneous and their capacity is bounded. Also, there is at least one vehicle in each warehouse and every vehicle is capable of satisfying the demand for fuel in multiple nodes. Second, the affected areas are prioritized based on a coefficient representing their relative importance compared to other areas. Third, according to the number of residential and commercial properties in each area the demand for the specified areas is identified and a penalty is considered for unsatisfied and/or lost demands. Forth, a coefficient, referred to α, is used in the model to represent the percentage of the demand in each affected area that is met prior to the critical time to supply fuel. The last assumption is that the directions remain constant.

Our proposed framework has the flexibility to adopt to other natural disasters such as floods, tornadoes, volcanic eruptions, hurricanes, tsunamis, storms or other geologic processes, however some assumptions must be modified. In fact, although the type of natural crises is different, they have many points in common. A failure to quickly respond to these crises or making an incorrect decision will have serious consequences. Therefore, it is necessary to design mathematical models which can realistically represent the complex conditions and constraints during these disasters.

3. Mathematical formulation

Nomenclature

Sets of indices:

I	Earthquake-affected areas
O	Warehouses
K	Vehicles

Parameters:

p_i	Penalty of unsatisfied demand for the area *i*
pp_i	Penalty of lost demand for the area *i*
W_i	Relative importance of the area *i*
D_i	Demand of the area *i*
C_k	Capacity of the vehicle *k*
l_i	Critical time for supplying the demand of the area *i*
t_{ij}	Travel time between the area *i* and the area *j*
t_{oj}	Travel time between the warehouse *o* and the area *j*
α	Percentage of demand for each area that is satisfied before l_i
a_{ok}	= 1, If the vehicle *k* is available in the warehouse *o*, otherwise = 0
M	A large number

Variables:

X_{ik}	Total quantity of the fuel transferred to the area *i* by the vehicle *k*
XX_{ik}	Part of the demand transferred to the area *i* by the vehicle *k* before l_i
Y_{ijk}	= 1, If the vehicle *k* goes from the area *i* to the area *j*, otherwise = 0
YY_{Ojk}	= 1, If the vehicle *k* goes from the warehouse o to the area *j*, otherwise = 0
YYY_{jok}	= 1, If the vehicle *k* goes from the area *j* to the warehouse o, otherwise = 0
s_i	Level of satisfied demand in the area *i*
γ_{ij}	Absolute value of the difference between satisfied demands in the areas *i* and *j*
β_{ik}	Determining arrival time before l_i or after
ls_i	Lost demand of the area *i*

AT_{jk}	Arriving time to the area *j* by the vehicle *k*
ATT_{ijk}	=1, If the vehicle *k* goes to the area *j* from the area *i*, otherwise 0.

The fuel distribution problem in this study is formulated by a bi-objective non-linear programming model with multiple constraints. The defined constraints can be divided to two groups. The first and the most important group is related to the transport vehicles and temporary warehouses. However, the second group of constraints is about the vehicles' arrival time to the affected areas. The formulation of the model is given as follows:

$$Minimise \sum_i \sum_k W_i \times \frac{(X_{ik} - XX_{ik})}{D_i} + \sum_i W_i \times \frac{ls_i}{D_i} \qquad (1)$$

$$Minimise \sum_i \sum_j \gamma_{ij} \qquad (2)$$

Subject to:

$$s_i = \sum_k X_{ik}/D_i \qquad (3)$$

$$\gamma_{ij} \geq s_i - s_j \qquad \forall i,j \qquad (4)$$

$$\gamma_{ij} \geq s_j - s_i \qquad \forall i,j \qquad (5)$$

$$\sum_o YY_{ojk} + \sum_i Y_{ijk} \leq 1 \qquad \forall j,k \qquad (6)$$

$$\sum_o YY_{ojk} + \sum_{\mathrm{i}} Y_{ijk} = \sum_{\mathrm{i}} Y_{jik} + \sum_o YYY_{jok} \qquad \forall j,k \qquad (7)$$

$$\sum_j YY_{ojk} \leq M * a_{ok} \qquad \forall o,k \qquad (8)$$

$$\sum_i \sum_j YY_{ijk} \leq M * \sum_j \sum_o YY_{ojk} \qquad \forall k \qquad (9)$$

$$\sum_o \sum_j YY_{ojk} \leq 1 \qquad \forall k \qquad (10)$$

$$AT_{jk} = \sum_i (ATT_{ijk} + t_{ij} * \mathrm{Y_{ijk}}) + \sum_o (YY_{ojk} * \; tt_{oj}) \qquad \forall j,k \qquad (11)$$

$$l_i - AT_{ik} \leq M * \beta_{ik} \qquad \forall i,k \qquad (12)$$

$$AT_{ik} - l_i \leq M * (1 - \beta_{ik}) \qquad \forall i,k \qquad (13)$$

$$XX_{ik} * \beta_{ik} \leq X_{ik} \qquad \forall i,k \qquad (14)$$

$$\sum_k X_{ik} + ls_i = D_i \qquad \forall i \qquad (15)$$

$$\sum_k XX_{ik} \geq \alpha * D_i \qquad \forall i \qquad (16)$$

$$\sum_j X_{jk} \leq C_k \qquad \forall k \qquad (17)$$

$$X_{jk} \leq M * (\sum_{i} Y_{ijk} + \sum_{o} YY_{ojk}) \quad \forall k,j \quad (18)$$

$$Y_{ijk} + Y_{jik} \leq 1 \quad \forall k,j,i \quad (19)$$

$$Y_{ijk} \leq \sum_{o} YY_{oik} + \sum_{r} Y_{rik} \quad \forall i,j,k \quad (20)$$

$$Y_{ijk}, YY_{ojk}, YYY_{jok}, ATT_{ijk} \in \{0,1\} \\ X_{ik}, XX_{ik}, s_i, \gamma_{ij}, \beta_{ik}, ls_i, AT_{jk} \geq 0 \quad \forall i,j,k,o \quad (21)$$

Expression (1) describes the minimization of the total unsatisfied and lost demands in different damaged areas, where W_i represents the relative importance of the area i. Expression (2) represents the goal of a fair distribution of fuel in damaged areas by minimizing the difference between satisfied demands in different areas. Constraint (3) represents the total proportion of satisfied demand in damaged areas. This proportion is defined as the fraction of fuel demand which is satisfied in each area. Constraints (4) and (5) illustrate the difference between the satisfied demands in different areas. Constraint (6) guarantees that a vehicle enters each area from the warehouse or other areas on at least one occasion. Constraint (7) ensures that, if any vehicle entering into an area is to leave that area, then it will go to other areas or return to a warehouse. Constraint (8) shows that if the vehicle k exists in the warehouse o, then it can enter an area. Constraint (9) indicates that any vehicle can enter into one of the areas if it has left a warehouse. Constraint (10) demonstrates that each vehicle can exit from a warehouse on only one occasion. Constraint (11) defines the arriving time to the area j. Constraints (12) and (13) ascertain whether the arriving time to an area is before the critical time or after. Constraint (14) shows that if arrival time of the vehicle k to the area i is before the critical time, then X_{ik} takes on a positive value. Constraint (15) represents the demand of each affected area. Constraint (16) states that the amount of fuel distributed to an area before the critical time equals at least α percent of the total demand in that area. Constraint (17) is related to the capacity of the vehicles. Constraint (18) states that each vehicle can transfer the fuel to affected areas only from a warehouse or other areas. Constraint (19) guarantees that a loop will not be created. Constraint (20) states that the vehicle k can go from the area i to the area j as long as it enters the area i either from a warehouse or other areas. Constraint (21) states the type of decision variables and their restrictions.

Constraints (11) and (14) are non-linear and should be converted into linear equations. Constraint (11) is converted into three linear equations as follows:

$$ATT_{ijk} \leq M * Y_{ijk} \quad \forall i,j,k \quad (22)$$

$$ATT_{ijk} \geq AT_{jk} - M * (1 - Y_{ijk}) \quad \forall i,j,k \quad (23)$$

$$ATT_{ijk} \leq AT_{jk} + M * (1 - Y_{ijk}) \quad \forall i,j,k \quad (24)$$

Constraint (22) states that if the vehicle k goes to the area j from the area i, then the value of Y_{ijk} will be equal to 1 and ATT_{ijk} will take on a positive value. Otherwise, Y_{ijk}=0. In order to determine the value of ATT_{ijk}, constraints (23) and (24) were defined. Similarly, constraint (14) is also converted into three linear functions as follows:

$$XX_{ik} \leq M * \beta_{ik} \quad \forall i,k \quad (25)$$

$$XX_{ik} \geq X_{ik} - M * (1 - \beta_{ik}) \quad \forall i,k \quad (26)$$

$$XX_{ik} \leq X_{ik} + M * (1 - \beta_{ik}) \quad \forall i,k \quad (27)$$

Constraint (25) shows that if the vehicle k enters the area i before the critical time, XX_{ik} will take on a positive value. Otherwise XX_{ik} = 0. In order to determine the value of XX_{ik}, constraint (26) and (27) were defined.

4. The solution approach

In this section, a solution approach is proposed to solve the optimization problem. In general, two approaches are adopted to solve a multi-objective optimization model. The first approach is known as scalar approach. In this approach, the multi-objective problem is transformed into a single-objective optimization problem. Some well-established methods such as aggregation method, weighted metric method, goal programming (GP) method, goal attainment method and the ϵ-constraint method follow this approach. The second approach is known as dominance-based approach that adopts the concept of dominance in the fitness evaluation. The most important feature of the dominance-based approach is that it does not require to convert a multi-objective optimization problem into a single-objective optimization problem. In each run, it generates a diverse set of Pareto solutions in the concave portions of the convex hull of feasible objective space. There are many metaheuristic evolutionary algorithms that follow the dominance-based approach. NSGA-II – which is based on the Genetic Algorithm – and MOPSO – which is based on the particle swarm optimization – are two of the most popular and useful algorithms for solving multi-objective problems [39].

As MOEAs are able to quickly find Pareto optimal solutions in a single simulation run, we employ a MOEA to solve our bi-objective non-linear optimization model. In the literature, several researchers have recommended the NSGA-II as an effective MOEA to solve similar problems. Therefore, in this study, we attempt to solve the model using this approach. Moreover, the MOPSO algorithm is also employed due to the absence of a benchmark to use for validation of the results.

4.1. NSGA-II

The NSGA-II algorithm is one of the most efficient and popular MOEAs which was introduced by Deb *et al.* in 2000 [40]. It ranks and also sorts Pareto solutions by employing non-dominated sorting and crowding distance operators. In the first step, the tournament election, recombination (crossover) and mutation operators are applied to create the offspring Q_t from the parent population P_t. Then, objective functions for each individual are evaluated and the population is ranked based on a non-domination sorting procedure to generate Pareto fronts. Finally, the new population is filled by solutions of different non-dominated fronts F_i based on their ranks. If the number of solutions in the last allowed front is found to be more than the remaining slots in the new population, they will be chosen, which also have a larger crowding distance. At the end of each run of the algorithm, a set of non-dominated Pareto solutions are obtained. The schematic representation of the NSGA-II solution procedure is shown in Figure 2.

Figure 2

Figure 2. A schematic representation of the NSGA-II solution procedure.

The pseudo-code of main steps of the NSGA-II solution procedure is presented here for reference.

NSGA-II algorithm
1: Determine the NSGA II parameters consisting the size of population, crossover and mutation rate, etc.;
2: Generate P random populations
3: Check and modify each individual's feasibility

```
Calculate the value of objectives
Determine the rank and calculate crowding distance for each solution
Select chromosomes by binary tournament selection
Use crossover and mutation operators
Create Q offspring
For i = 1 to "max number of iteration"
    for each member of the population
        Determine the rank of the solution
        Sort solutions from the current front by crowding distance;
        end
    Select the best non-dominated solutions for next generation
    Create next generation
    Binary tournament selection
    Recombination and mutation
    end
End
```

4.1.1. Solution representation in NSGA-II

As this research deals with the distribution of fuel during an earthquake, each chromosome will represent the order of the amount of fuel that is delivered to an area by a vehicle. Therefore, if we assume that there exist K vehicles and I regions, it can be inferred that the chromosome has $2K$ rows and I columns. Each pair of rows is related to one vehicle such that the upper row represents the amount of fuel delivered by a vehicle to a region, and the bottom row pertains to the order of fuel reception. As an illustration, Figure 3 shows a typical solution with K vehicles and seven regions. The zero values imply that the corresponding region does not receive any fuel from the vehicles.

Figure 3

Figure 3. Chromosome representation.

4.1.2. Crossover

As mentioned earlier, the solution approach presented in this study involves $2K$ rows and I columns, where each pair of rows indicates the amount and the order of fuel that is to be delivered to a region by a vehicle. Here, we use the two-point crossover operator, as shown in Figure 4. Therefore, the two selected parts combine and generate offsprings. After combining parents, if two equal values appear in an order row for a vehicle, we then change one of them randomly to the smallest value that does not exist in that row. For example, if the appeared values are 1,0,0,4,4,3,0, we choose one of four numbers randomly (first one in this case) and change it with 2. Therefore, the modified results are 1,0,0,2,4,3,0.

Figure 4

Figure 4. The generation of offsprings from parents by two-point crossover operators.

4.1.3. Mutation

Mutation operators act upon a single individual as unary operators. Selected examples of a population change slightly by Mutations. The main purpose of this operator is to prevent algorithm from getting trapped into a local optimal as well as to increase its diversification (see [41]). In this study, we use swap operations and the procedure is as follows.

1. For each vehicle $k \in \{1,...,K\}$ **do.**
2. Randomly select one of the regions that received fuel from vehicle *k*.
3. Randomly select one of the regions with zero value (does not receive fuel from vehicle *k*). If there is no zero value, select a region randomly.
4. Swap the position of these selected genes.
5. End

Figure 5 shows an example of the swap operation.

Figure 5

Figure 5. Generating new chromosome by swap operation.

4.2. Multi-objective particle swarm optimization (MOPSO)

MOPSO was first introduced by Coello and Lechuga [42] as one of the fastest algorithms to solve multi-objective optimization problems. In the first step, the algorithm begins with N_{pop} randomly generated particles (solutions) where each particle has its current position and velocity. Denote by $S_i^t = \{n_i^t, h_i^t\}$ and $v_i^t = \{v_{i,1}^t, v_{i,2}^t\}$, respectively, the position and velocity of the particle i ($i = 1,...,N_{pop}$) at iteration $1,...,it_{max}$. In the second step, the algorithm evaluates each individual based on a fitness function. Afterwards, the non-dominated Pareto solutions are selected and stored in an external repository (hereafter referred to as REP). The REP regulates the number of non-dominated solutions by two control components, including an archive controller and a grid. The archive controller checks whether or not a new solution should be added to the archive. In each iteration of the algorithm, new solutions are compared one by one with all existing solutions in the REP and if it is dominated by any solution, it will then be discarded; otherwise, the new solution will be added to the archive. After adding the new solution, if any solution is found to be dominated it will be discarded. It is assumed that REP has limited capacity; therefore, the decision about adding a new solution is made using an adaptive grid method when it reaches its limit. The ultimate objective of using an adaptive grid method is to have a well-distributed Pareto set. The space of these objectives is divided into regions that will change based on the solutions in the REP, i.e., when a new solution is found outside of the current grid, the grid will be updated and the individual situated within it will be relocated. The classical roulette wheel selection is applied in this situation to select a hypercube in which the selection probability of each hypercube is considered to be the inverse proportion of the number of repository members in the given hypercube. At a subsequent phase, a leader is determined randomly and the position of a particle is updated. Finally, the mutation operator is applied to increase the algorithm diversification and the best personal position is updated. The pseudo-code of main steps of the MOPSO solution procedure is presented here for reference.

MOPSO algorithm

1: Determine the MOPSO parameters involving population size, mutation rate, stopping criteria, etc.;
2: Generate the initial swarm
3: Check and modify the feasibility of each particle
4: Evaluate each particle
5: Determine the Non-dominated solutions and store them in the Rep
6: Construct the hyper-cubes via dividing the search space
7: Select a leader for each particle from the repository by using a roulette wheel selection
8: Update the velocity of each particle using the below equations:

$$v_i^t := w_t * v_i^{t-1} + C_1 * r_1 * \left(pBest_i^t - s_i^{t-1}\right) + C_2 * r_2 * \left(gBest^t - s_i^{t-1}\right)$$

$$w_t = w_{max} - \frac{w_{max} - w_{min}}{It_{max}} t$$

9: Employ the mutation operators and generate a new offspring
10: Update the position of each particle using the below equation:

$$S_i^{t+1} := S_i^t + v_i^t$$

11: Update the personal best of each particle
If S_i^t dominates $pBest_i^t \rightarrow pBest_i^t = S_i^t$
12: Update Rep at the end of each iteration
13: **If** not all the termination criteria are satisfied, then return to 4
END

4.2.1. Mutation

In order to increase the diversification of the algorithm, three types of mutation operators are proposed in this paper. The first type inverses the order of fuel delivered by each vehicle. The second type uses swap operator similar to that in the previous section, and the third type randomly selects information about one region in one individual and inserts it randomly between other regions. Figure 6 shows the mutation operators of the MOPSO solution approach.

Figure 6

Figure 6. The mutation operators of the MOPSO solution approach.

4.3. Feasibility checking procedure

After generating new solutions by the NSGA-II algorithm or the MOPSO algorithm, it is important to ascertain the solutions' feasibility. If the solution is not feasible, it will be modified. The pseudo-code for modifying an infeasible solution is presented here for reference.

1. For each vehicle $k \in \{1,\ldots,K\}$ **do**
2. While $\sum_{i=1}^{I} x_{ik} > c_k$ **do**
3. max $\{x_{1k},x_{2k},\ldots,x_{Ik}\} = x_{max}$
3. if $x_{max} > \sum_{i=1}^{I} x_{ik} - c_k$ then
4. $x_{max} := x_{max} - (\sum_{i=1}^{I} x_{ik} - c_k)$
5. Else if
6. $x_{\max} := 0$
7. End while

4.4. Performance metrics for NSGA-II and MOPSO algorithms

There are different metrics used for comparing the performance of non-dominated Pareto solutions obtained by NSGA-II and MOPSO algorithms. The most important performance metrics include: spacing metric, inverted generational distance, number of Pareto solutions, and CPU time in seconds. The following subsections provide a succinct description of these criteria.

4.4.1. Spacing metric (Δ)

The spacing metric was introduced by Deb [43]. It computes the standard deviation of the distance from each member of non-dominant Pareto solutions in order to measure how spread the solutions are in the entire region. In other words, spacing metric shows the effectiveness with which the non-dominated Pareto solutions are distributed in the search space. A low value of spacing metric means that the members of the Pareto front are spread in a uniform manner. The metric is defined as follows:

$$\Delta = \sum_{i=1}^{|n|} \frac{|d_i - \bar{d}|}{|n|} \tag{28}$$

where $d_i = min_{k \in n, k \neq i} \sqrt{\sum_{m=1}^{2} \left(f_m^i - f_m^k\right)^2}$, $\bar{d} = \sum_{i=1}^{n} \frac{d_i}{|n|}$, n represents the number of non-dominated solutions in the Pareto front and f_m^i denotes the amount of the m^{th} objective function for the i^{th} non-dominated Pareto solution.

4.4.2. Inverted generational distance (IGD)

IGD is a metric representing the convergence and diversity of solutions. This metric is calculated by following equation [44]:

$$IGD(H, H^*) = \frac{\sum_{x \in H^*} min_{y \in H} dist(x, y)}{|H^*|} \tag{29}$$

where H is the value of objective functions calculated by MOEA, H^* is a set of solutions that are uniformly distributed in optimal Pareto front, and $dist(x, y)$ is the Euclidean distance between solutions x and y. This metric calculates average minimum distance between each solution in H^* with those in H. The smaller value of IGD, the better convergence and diversity of H.

4.4.3. Number of Pareto solutions (NPS)

NPS metric is used to measure the cardinality of an algorithm. The greater the number of Pareto solutions, the greater the number of decision-making alternatives available to the decision maker. Therefore, larger values of NPS metric indicate better performance of the algorithm.

5. Computational results

This section aims to (1) present a real world application, (2) tune the algorithms' parameters using the Taguchi method, and (3) evaluate the quality of Pareto front solutions calculated by each algorithm. To these aims, first the problem parameters are introduced in section 5.1. Subsequently, the best values of these parameters are determined in section 5.2. Finally, the problem is solved and different aspects of the obtained non-dominated Pareto solutions are compared with respect to the aforementioned performance metrics in section 5.3.

5.1. Case study

In this subsection, a hypothetical earthquake with actual dimensions and realistic data in Yazd city of Iran is presented as a case study. Yazd is a desert city in the center of Iran and is currently the 15th largest city in the country. Figure 7 shows the geographical location of Yazd province in Iran.

Figure 7

Figure 7. Geographical location of Yazd Province in Iran.

The Yazd city suffers from several climatic challenges and problems caused by tectonic and seismic processes, which are briefly described in the following:

- Climatic challenges: Dry climate, low rainfall, extremely high evaporation, and severe water and wind erosion have led to the spread of deserts and sand dunes in the city. Also windstorms and large fluctuations in temperature during the day and in the summer and winter seasons have a profound effect on the physical destruction of walls and buildings.
- Problems caused by tectonic and seismic processes: The disasters such as flood and earthquake rarely happen in Yazd, but if either of these natural disasters occurs, there will be considerable destruction.

Many faults have been detected in Yazd province, but the most well-known ones include the Ardakan north-south fault and the Dehsir-Baft fault. The earthquake epicenters and major faults of Yazd province in Iran are shown in Figure 8.

Figure 8

Figure 8. Seismicity of Yazd province in Iran [45]**.**

In the case of an earthquake in Yazd province, the following actions for fuel distribution will be taken:

- A quick notification to responsible organizations: The status of the structure of the fuel resources, the fuel transfer lines, the amount of fuel to be delivered, the fuel transfer and distribution paths, the status of the existing tankers, etc. will be studied;
- A rapid restoration of the earthquake-affected infrastructure to normal condition;
- Coordination and ensuring coordinated actions of executive authorities based on instructions.

There are ten regions in Yazd province. The demand for fuel in each region is calculated according to the number of households in that region. There exit three fuel warehouses in the province which have 5, 6, and 6 vehicles, respectively. The location of these ten regions and three warehouses in Yazd province are shown in Figure 9.

Figure 9

Figure 9. Location of ten regions and three warehouses in Yazd province in Iran.

Table 2 gives the fuel demand in each region, the travel time between warehouses and regions as well as the travel time between regions. Critical time for supplying the fuel is considered to be 100 minutes. Each household is assumed to consist of 4 members and require at least 5 liters of fuel.

Table 2

Table 2. Model parameters for ten regions and three warehouses.

5.2. Parameter tuning

In this study, two algorithms of NSGA-II and MOPSO were used to find the Pareto optimal solutions. As MOEAs are often sensitive to their parameters' values, the optimal level of each parameter is determined by Taguchi's design of experiment (DOE) approach. This approach has been applied as an effective tool for full factorial experiments [46]. The parameters (factors) that were considered for NSGA-II algorithm include: population size (PS), number of iteration (NoI), mutation rate (MR) and crossover rate (CR). However, the parameters considered for MOPSO algorithm are: population size (PS), number of iteration (NoI), repository size (RS) and leader selection pressure (LSP). Three different classes of objectives are defined in Taguchi method: smaller is the better, larger is the better, and the nominal is the best. The optimum level of a factor is the level that results in the highest value of the signal-to-noise (S/N) ratio. S/N calculates the amount of variation in the process. In this research, since the goal is to minimize S/N, the smaller-the-better type of response is utilized, where S/N is defined by:

$$S/N = -10 \times log\left(\frac{S(Y^2)}{n}\right) \tag{30}$$

where Y is the value of each response, n is the number of problem solving (runs), and $S(Y^2)$ is the summation of the responses Y^2. For each parameter, three levels are considered and presented in Table 3.

Table 3

Table 3. Three levels of each parameter considered in the orthogonal experiment.

To find the best level of each parameter, we replicate the algorithm three times for each run experiment. Then, the values of the first objective (total penalties of unsatisfied and lost demands) and the second objective (fair distribution of fuel in affected areas) are transformed into S/N ratios. We use an L9 Taguchi orthogonal array to tune them by the Minitab software and their responses are presented in Table 4.

Table 4

Table 4. Calibration process of NSGA-II and MOPSO algorithms.

The Taguchi S/N ratio plots for the NSGA-II and MOPSO algorithms are presented in Figure 10 and Figure 11, respectively.

Figure 10

Figure 10. Taguchi S/N ratio plot for NSGA-II algorithm.

Figure 11

Figure 11. Taguchi S/N ratio plot for MOPSO algorithm.

We used Figure 10 and Figure 11 to select the optimal values of the parameters according to three levels. The optimal values of the parameters in two algorithms are given in Table 5.

Table 5

Table 5. Optimal values of the parameters in NSGA-II and MOPSO algorithms.

The responses for S/N ratios in NSGA-II and MOPSO algorithms are given in Table 6 and Table 7, respectively. As the ranks show, the mutation rate (MR) in NSGAII algorithm and the population size (PS) in MOPSO algorithm have the most influence on the S/N ratio, respectively.

Table 6

Table 6. Responses for S/N ratios in NSGA-II taking into account that smaller is a better state.

Table 7

Table 7. Responses for S/N ratios in MOPSO taking into account that smaller is a better state.

5.3. Analysis of the results

In this subsection, we evaluate the performance of the proposed solution algorithms. For this purpose, both algorithm are run for ten times and then their performance is compared against each other in terms of four criteria: (1) spacing metric (Δ), (2) inverted generational distance (IGD), (3) number of Pareto solutions (NPS), and (4) the required CPU time in seconds. These four performance measures are obtained by using the parameter-tuned algorithms on all ten replications. Table 8 presents the results of ten runs for NSGA-II and MOPSO algorithms. The last two rows in the table show the average (*Avg*) and the standard deviation (*Std*) of the values for these four metrics in ten replications.

Table 8

Table 1. Experimental results of ten runs for NSGA-II and MOPSO algorithms.

According to the results reported in Table 8, the NSGA-II algorithm has smaller value in Δ and IGD metrics but it has larger value in NPS metric. Therefore, it can be concluded that the NSGA-II algorithm generates more efficient Pareto solutions compared to the MOPSO algorithm. Also, each Pareto set is ranked based on four metrics (Δ, IGD, NPS and CPU time) by means of a popular MCDM method called TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) [47]. Figure 12 compares the top-ranking Pareto sets in ten runs for NSGA-II and MOPSO algorithms.

Figure 12

Figure 12. The best Pareto solutions in ten runs for NSGAII and MOPSO algorithms.

In addition, one-way analysis of variance (ANOVA) is used to determine whether there is any significant difference between the performances of NSGAII and MOPSO algorithms in terms of the abovementioned metrics. Tables 9-12 present the results of the ANOVA along with the values of the corresponding *p*-values for four performance metrics, including Δ, IGD, NPS and CPU time at 95% confidence level.

Table 9

Table 9. ANOVA for performance metric Δ .

Table 10

Table 10. ANOVA for performance metric IGD.

Table 11

Table 11. ANOVA for performance metric NPS.

Table 12

Table 12. ANOVA for performance metric CPU time.

Though significant differences are observed between the NSGAII and MOPSO algorithms in term of spacing metric (Δ), the differences in terms of IGD, NPS and CPU time were negligible. Figures 13–16 show the box plots of the four performance metrics Δ, IGD, NPS and CPU time for the proposed algorithms.

Figure 13

Figure 13. The box-plot for performance metric Δ .

Figure 14

Figure 14. The box-plot for performance metric IGD.

Figure 15

Figure 15. The box-plot for performance metric NPS.

Figure 16

Figure 16. The box-plot for performance metric CPU time.

5.4. Solving model by a weighted sum method (WSM)

In this subsection, the proposed bi-objective optimization model is solved by a WSM and the Pareto frontiers are calculated by considering different values for the weights. In order to solve a multi-objective problem with inconsistent objectives, several methods have been proposed in the literature. L_P-metrics is a popular method for solving multi-objective optimization problems. This is formulated as Eq. (31) for two objectives of Z_1 and Z_2 and the case p=1:

$$\min Z_3 = \left[w.\frac{Z_1 - Z_1^*}{Z_1^*} + (1-w).\frac{Z_2 - Z_2^*}{Z_2^*} \right], \tag{31}$$

where Z_1^* and Z_2^* denote the ideal solutions for total penalties of unsatisfied and lost demands and fair distribution of fuel in earthquake-affected areas, respectively. The model has been implemented in GAMS (General Algebraic Modeling System) software (https://www.gams.com/). The results of the objective functions according to different weight values are presented in Table 13.

Table 13

Table 2. Trade-off between two objective functions with different weight values.

Figure 17 compares the best Pareto sets found by the NSGA-II algorithm with those found by the WSM approach.

Figure 17

Figure 17. The best Pareto solution found by NSGA-II algorithm versus WSM.

As can be seen, the Pareto set produced by the NSGA-II algorithm has better coverage on solution space than the WSM approach. Therefore, we used the NSGA-II algorithm for the analysis of various scenarios.

5.5. Sensitivity analysis and managerial insight

In this subsection, we analyze how various scenarios considered by the National Disaster Management Organization (NDMO) of Iran can affect the Pareto set. With this respect, two types of scenarios are considered. The first scenario is about adding new vehicles to the existing warehouses, whereas the second scenario deals with building a new warehouse or distribution center.

5.5.1. Adding new vehicles

In this subsection, we investigate how the number of vehicles and their allocation to the existing warehouses will affect the objective functions. Table 14 presents nine possible cases where S_1, S_2 and S_3 represent different vehicle allocations, S_4, S_5 and S_6 represent adding a new vehicle, and S_7, S_8 and S_9 represent adding two new vehicles to the existing warehouses.

Table 14

Table 14. Nine possible cases for changing vehicle allocations and adding new vehicles to the warehouses.

Figure 18 compares the Pareto sets for current situation with those obtained for S_1, S_2 and S_3 cases. For S_1 and S_2 cases, we considered to reduce a vehicle from warehouse 1 and add it to warehouse 2 and warehouse 3, respectively. For S_3, we took two vehicles from the warehouse 1 and added them to warehouses 2 and 3. Although the regions around warehouse 1 have smaller population than the other regions, it can be seen from Figure 18 that the Pareto set for current situation has better performance than that for other cases. This can be due to the fact that the distance between warehouses 2 and 3 and the areas covered by warehouse 1 is very large. Thus, it can be concluded that the current decision for distribution of the vehicles between three warehouses has an acceptable performance.

Figure 18

Figure 18. Pareto sets for current situation (CS) versus S_1, S_2 and S_3.

Figure 19 shows the Pareto sets for three cases of S_4, S_5 and S_6 where NDMO adds a new vehicle to warehouses. As can be seen, the Pareto set for the case S_5 has better performance than the other two cases. Therefore, if NDMO decides to add a new vehicle, it will be better to allocate it to warehouse 2.

Figure 19

Figure 19. Pareto sets for current situation (CS) versus S_4, S_5 and S_6.

Finally, Figure 20 depicts the Pareto solutions when NDMO decides to add two new vehicles to warehouses. With regards to the results of the analysis, if NDMO gives priority to the first objective (i.e., minimizing the total unsatisfied and lost demands), the case S_7 will be chosen (i.e., adding a new vehicle to warehouse 2 and another new vehicle to warehouse 3).

Figure 20

Figure 20. Pareto sets for current situation (CS) versus S_7, S_8 and S_9.

5.5.2. Adding a new warehouse

In this subsection, we obtain the Pareto solutions for a scenario where NDMO builds a new warehouse in three possible locations (W_4^1, W_4^1, W_4^1) and adds three vehicles. Blue points in Figure 21 show the three candidate locations.

Figure 21

Figure 21. Candidate locations for building a new warehouse.

Table 15 shows the travel time between the candidate warehouse locations and earthquake-affected areas.

Table 15

Table 15. Travel time between the candidate warehouses locations and earthquake-affected areas.

Table 16 presents nine possible cases where S_{10}, S_{11} and S_{12} represent different vehicle allocations for W_4^1, S_{13}, S_{14} and S_{15} represent different vehicle allocations for W_4^2, and S_{16}, S_{17} and S_{18} represent different vehicle allocations for W_4^3. Here, we assume 20 vehicles are available.

Table 16

Table 3. Nine possible cases for adding a new warehouse.

Figures 22-24 show the Pareto sets for three candidate warehouse locations of W_4^1, W_4^2 and W_4^3 , respectively. As can be seen, adding a warehouse has a significant impact on the first objective function. From the data in Figure 22, the Pareto set for the case S11 will have better performance if NDMO decides to choose W_4^1 as the new warehouse location.

Figure 22

Figure 22. Pareto sets for current situation (CS) versus S_{10}, S_{11} and S_{12}.

It can be concluded from Figure 23 that the Pareto sets for the case S_{13} have better performance than other cases. It is also observed about warehouse W_4^2 that if NDMO decides to reduce the first objective from 0.6 to 0.57, the second objective will increase from 30 to 80.

Figure 23

Figure 23. Pareto sets for current situation (CS) versus S_{13}, S_{14} and S_{15}.

It can be concluded from Figure 24 that the Pareto sets for the case S_{17} have better performance than other cases.

Figure 24

Figure 24. Pareto sets for current situation (CS) versus S_{16}, S_{17} and S_{18}.

In Figure 25 we compared all nine cases associated with adding a new warehouse. It seems that S_{17} and S_{18} have better performance than other cases. Therefore, it is suggested NDMO builds a new warehouse at location W_4^3.

Figure 25

Figure 25. Pareto sets for current situation (CS) versus S_{10}–S_{18}.

6. Conclusion and future research

In this study, a novel bi-objective non-linear optimization model was developed to operate an efficient and effective supply chain network for fuel distribution during an earthquake event. The objective functions included: (*i*) minimizing the penalties due to both delayed and unsatisfied fuel demands and (*ii*) minimizing the difference between the satisfied demands in different earthquake-affected areas. Many realistic assumptions, such as the existence of several central depots, limited vehicle capacities, and emergency response before critical time were considered in the modeling. Two multi-objective evolutionary algorithms (MOEAs) – including a NSGA-II and a MOPSO – were proposed to find Pareto front solutions of the model solve the optimization problem. Moreover, the Taguchi's design of experiment (DOE) method was adopted to tune the parameters of these algorithms.

A case study of Yazd province in Iran in actual dimensions and realistic data was provided to demonstrate the applicability of the proposed framework and evaluate the performance of the two algorithms in terms of four performance metrics, namely, spacing metric, inverted generational distance, number of Pareto solutions, and CPU time. In order to validate the Pareto front solutions obtained from MOEAs, we solved the model by a weighted sum method (WSM) with different values for the weights. The results showed better performance of NSGA-II algorithm compared to MOPSO algorithm for solving the case study. Finally, a sensitivity analysis with different scenarios was conducted to understand the impact of vehicle allocation between warehouses on the optimal Pareto front solutions. According to various scenarios that were examined, it was found out that the warehouse number two and the warehouse number three were strategically more important than the warehouse number one. Therefore, it is suggested that the National Disaster Management Organization (NDMO) of Iran can significantly improve the quality of Pareto front solutions by purchasing a new vehicle and allocating it to the warehouse number two and reducing a vehicle from the warehouse number one and allocating it to the warehouse number three. It is also recommended if the organization decides to purchase two vehicles, a vehicle to be assigned to the warehouse number two and another to the warehouse number three. Also, three potential points were considered as possible locations to build a new warehouse. Nine scenarios were analyzed and it was shown how adding a new warehouse would change Pareto solution.

There are several research directions to further improve or extend our work. One of the suggestions can be to develop new MOEMs such as decomposition-based MOEA to solve the bi-objective optimization model (for further see [48, 49]). In addition, the proposed model can be extended by incorporating the vehicle routing decisions. Also, the results would be more realistic by capturing uncertainties associated with demand and travel time.

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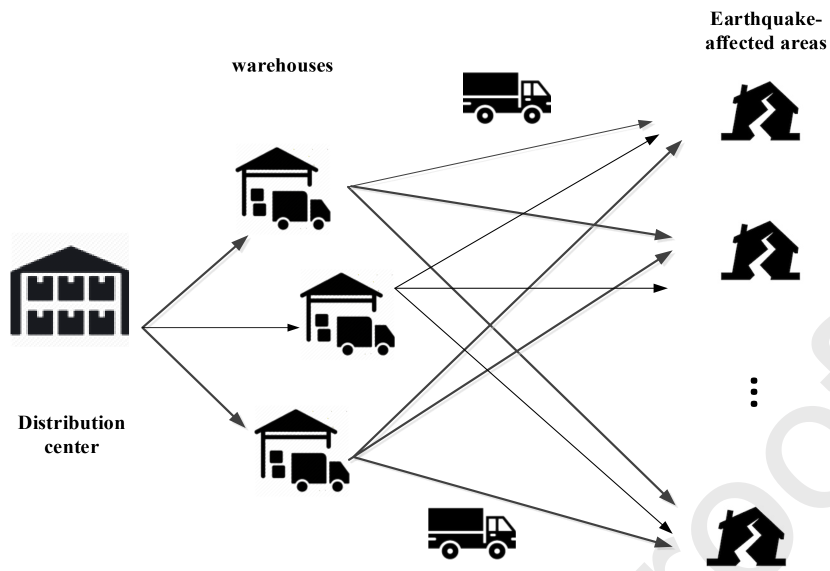

Figure 1. A fuel supply chain network in post-earthquake situations.

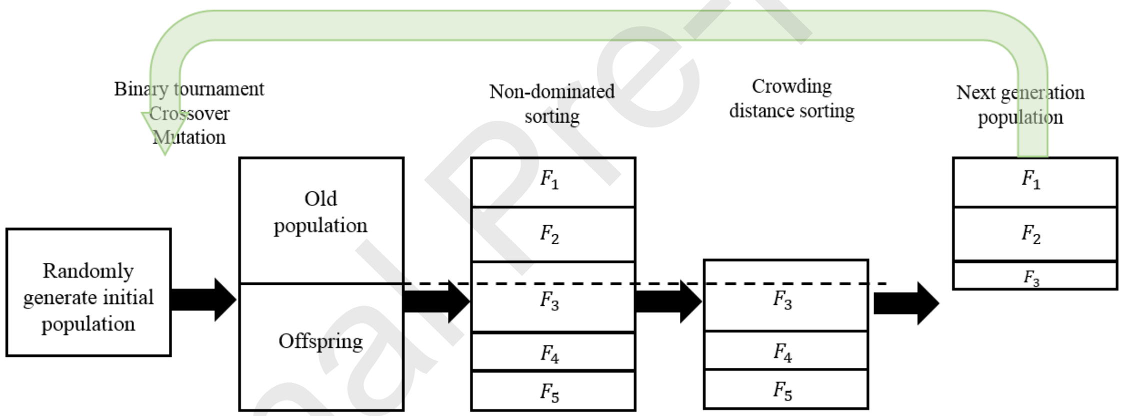

Figure 2. A schematic representation of the NSGA-II solution procedure.

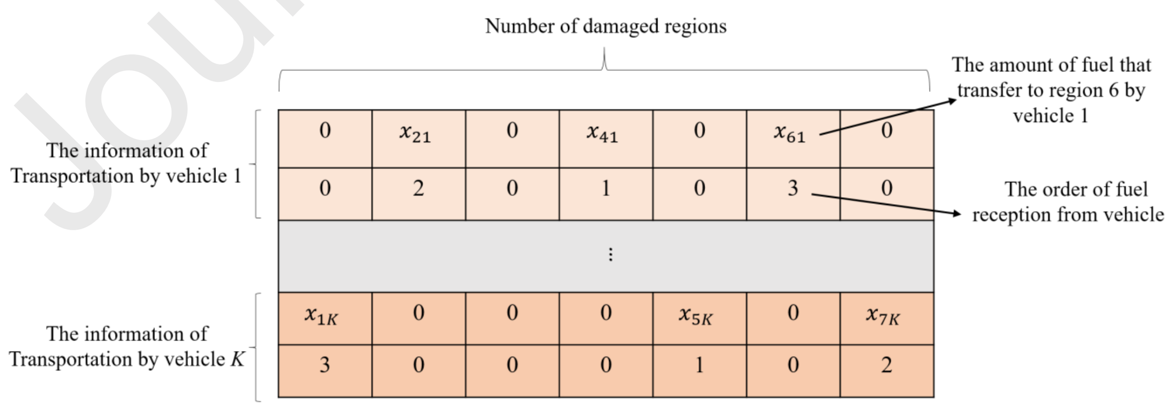

Figure 3. Chromosome representation.

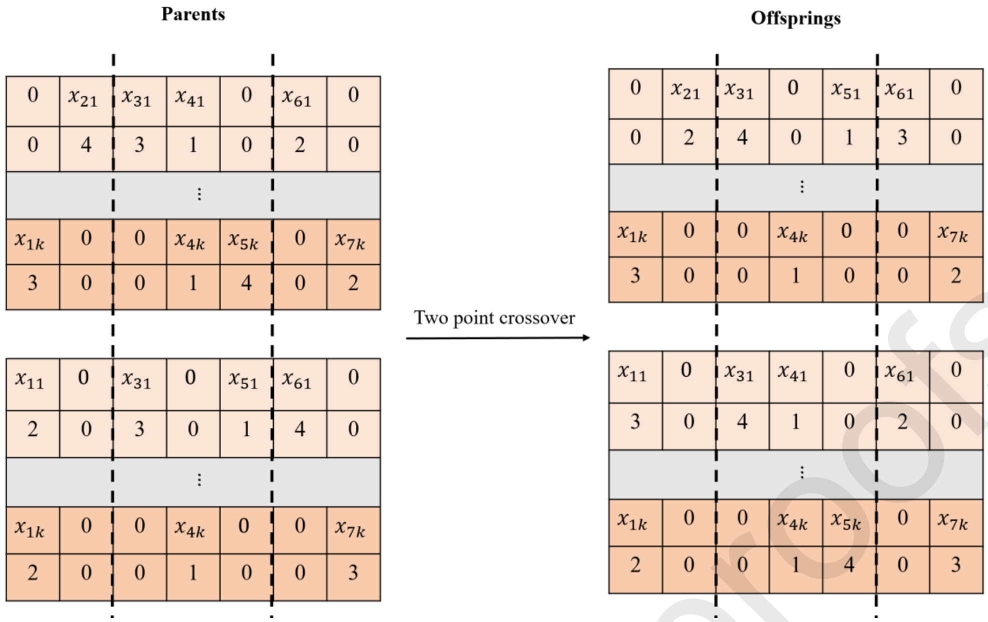

Figure 4. The generation of two offsprings from two parents by two-point crossover operators.

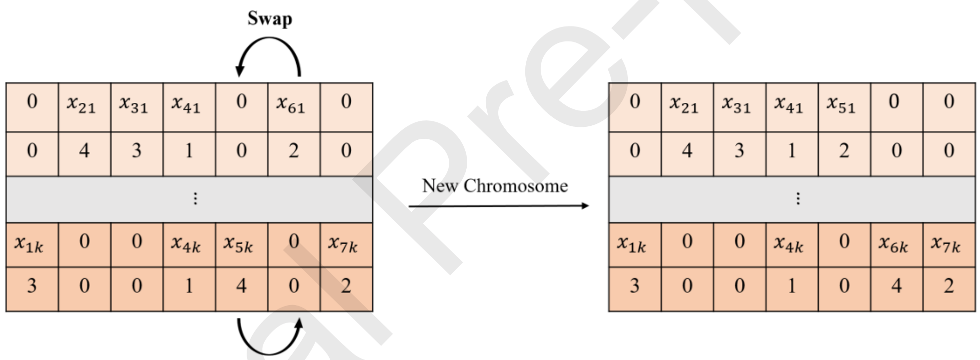

Figure 5. Generating new chromosome by swap operation.

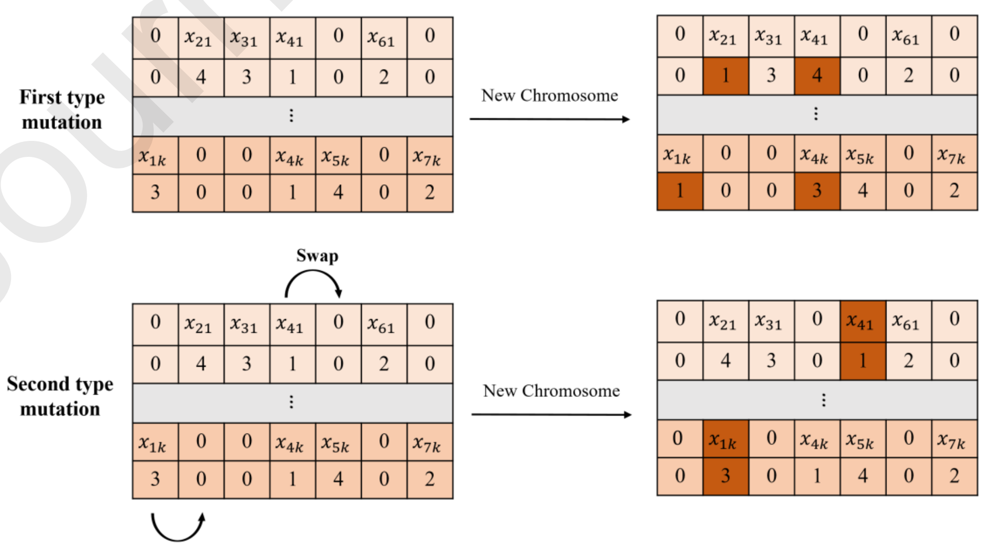

Figure 6. The mutation operators of the MOPSO solution approach.

Figure 7. Geographical location of Yazd Province in Iran.

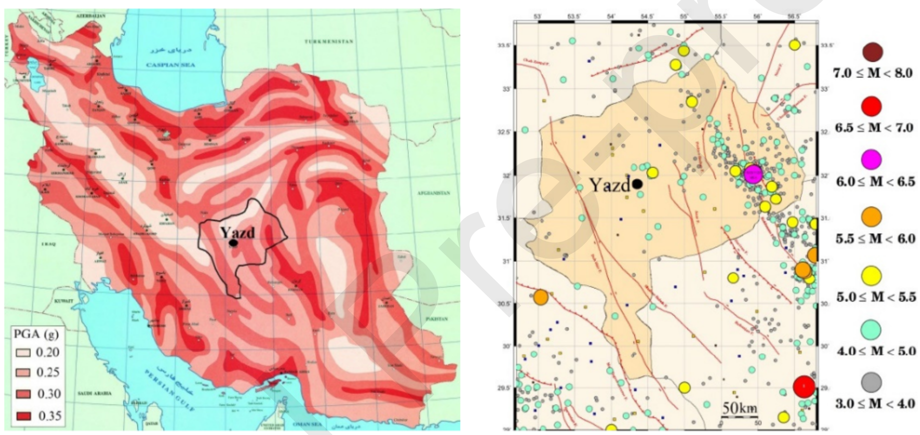

Figure 8. Seismicity of Yazd province in Iran [45]**.**

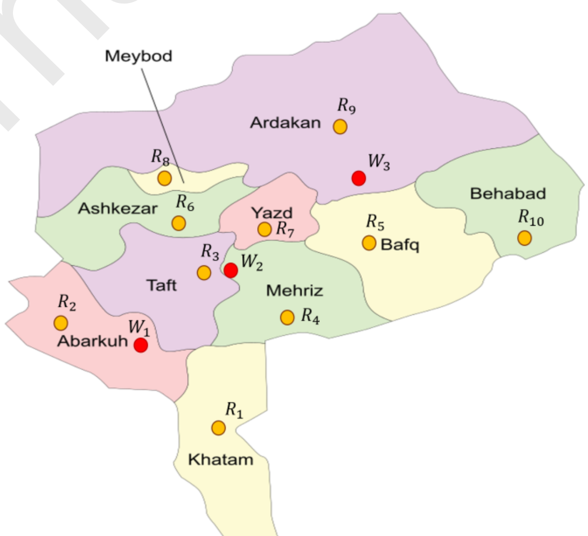

Figure 9. Location of ten regions and three warehouses in Yazd province in Iran.

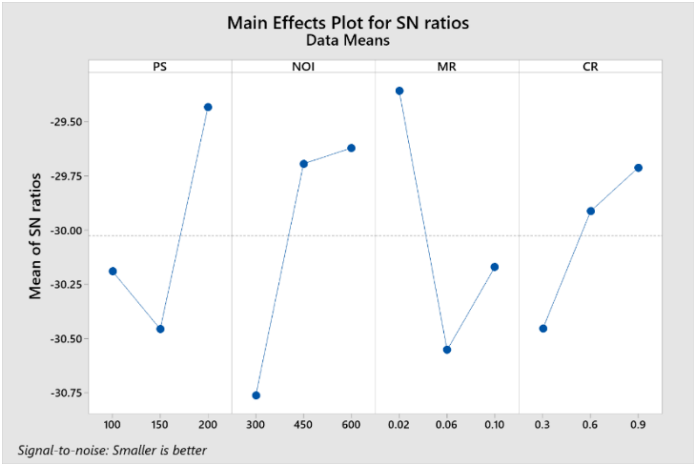

Figure 10. Taguchi S/N ratio plot for NSGA-II algorithm.

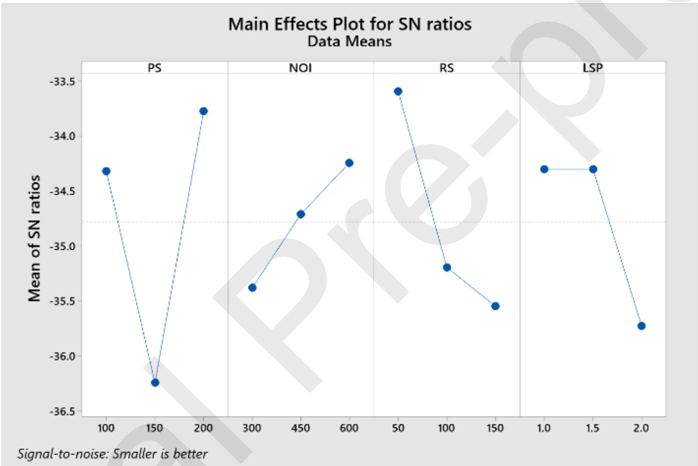

Figure 1. Taguchi S/N ratio plot for MOPSO algorithm.

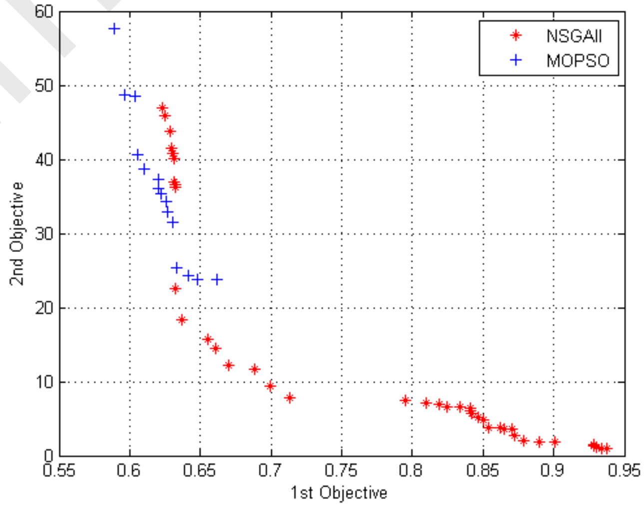

Figure 2. The best Pareto solutions in ten runs for NSGAII and MOPSO algorithms.

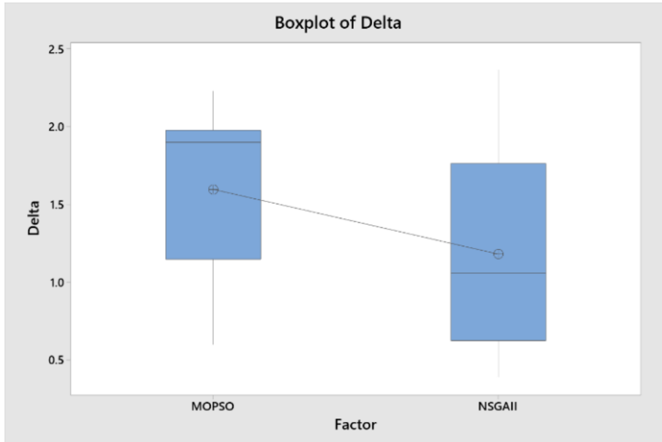

Figure 3. The box-plot for performance metric Δ.

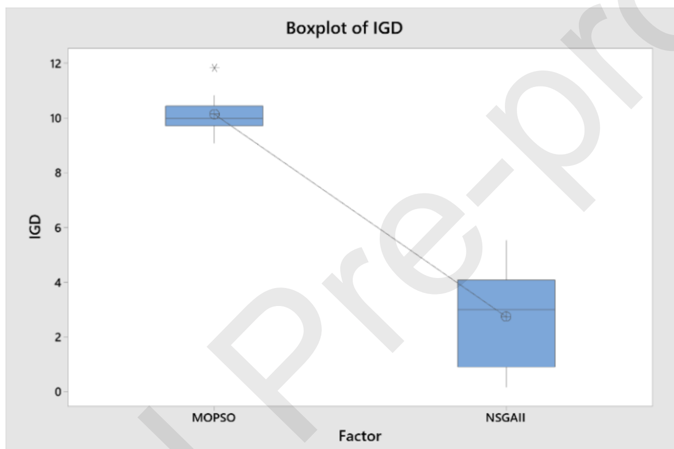

Figure 4. The box-plot for performance metric IGD.

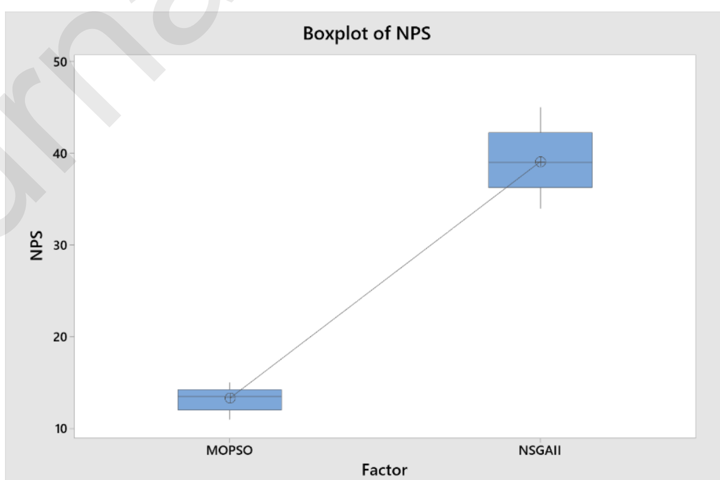

Figure 5. The box-plot for performance metric NPS.

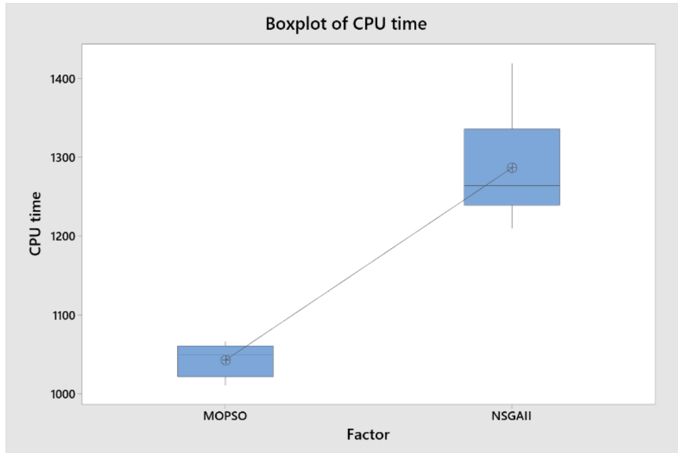

Figure 6. The box-plot for performance metric CPU time.

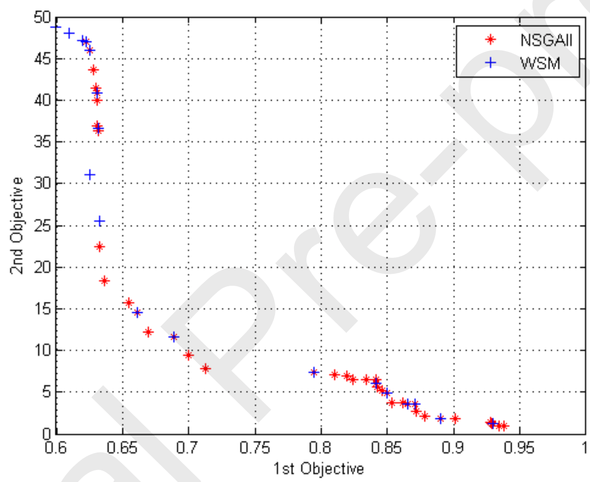

Figure 7. The best Pareto solution found by NSGA-II algorithm versus WSM.

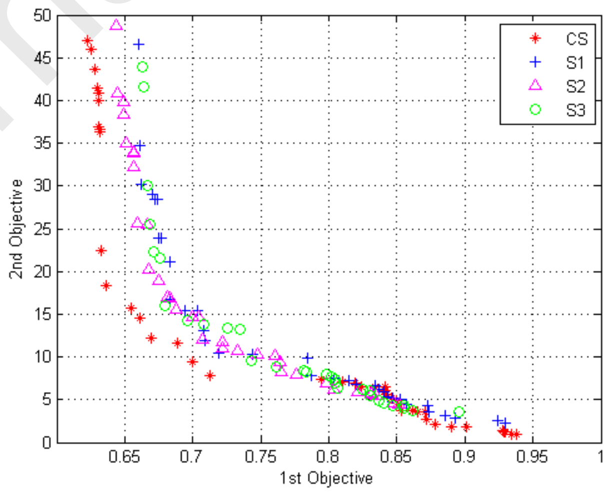

Figure 18. Pareto sets for current situation (CS) versus S_1, S_2 and S_3.

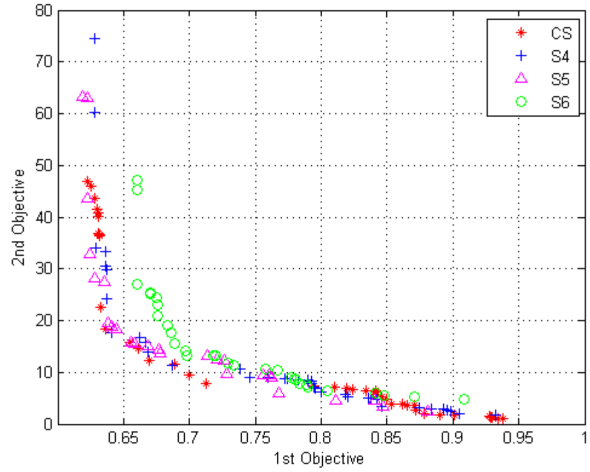

Figure 19. Pareto sets for current situation (CS) versus S_4, S_5 and S_6.

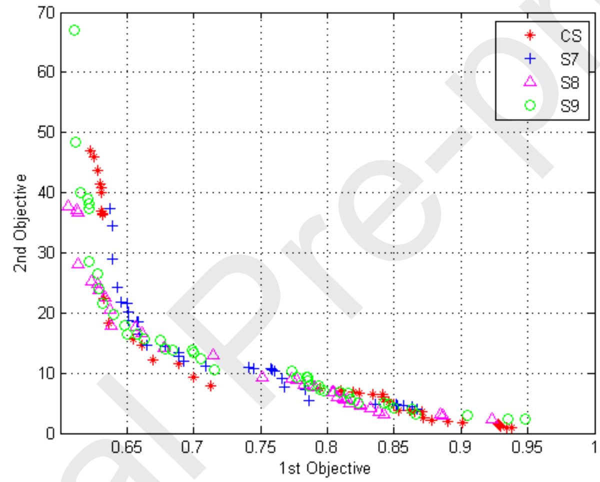

Figure 20. Pareto sets for current situation (CS) versus S_7, S_8 and S_9.

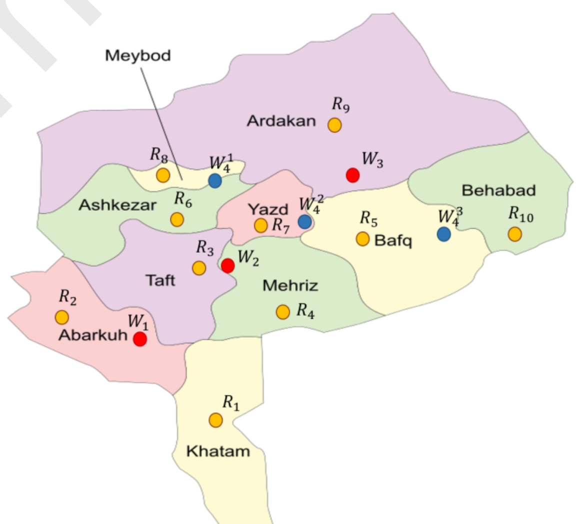

Figure 21. Candidate locations for building a new warehouse.

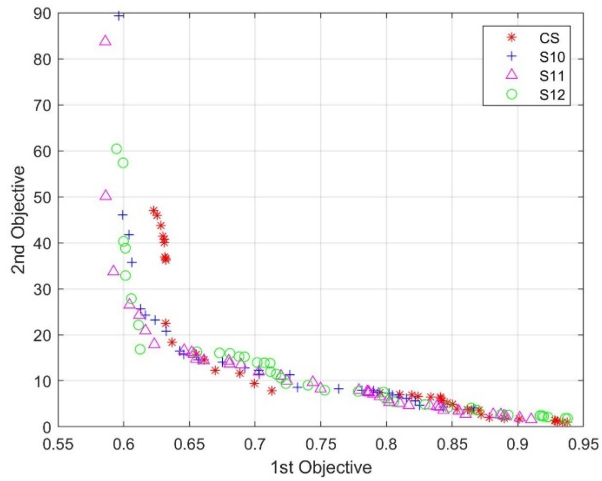

Figure 22. Pareto sets for current situation (CS) versus S_{10}, S_{11} and S_{12}.

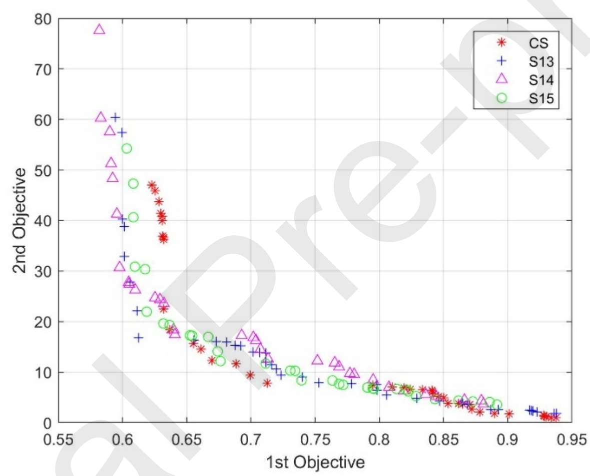

Figure 23. Pareto sets for current situation (CS) versus S_{13}, S_{14} and S_{15}.

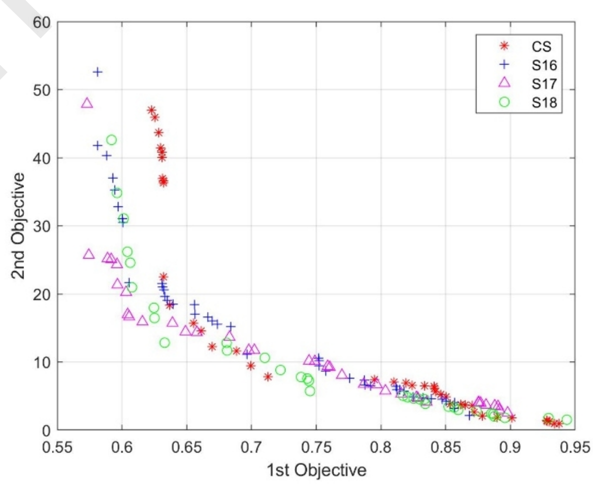

Figure 24. Pareto sets for current situation (CS) versus S_{16}, S_{17} and S_{18}.

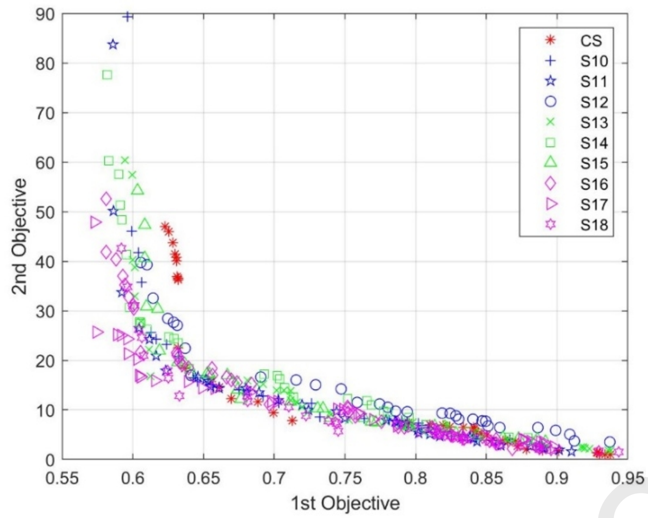

Figure 25. Pareto sets for current situation (CS) versus S_{10}–S_{18}.

Table 4. A summary of the studies about relief response in an earthquake.

Author (s)	Parameter type		Objective function		Solution method			distribution	
	Deterministic	Uncertain	single	multi	exact	heuristic	Meta-heuristic	Except fuel	fuel
Knott [12]	✓		✓					✓	
Knott [13]	✓		✓					✓	
Haghani and Oh [14]	✓			✓		✓		✓	
Barbarosoğlu *et al.* [15]		✓		✓	✓			✓	
Barbarosoglu and Arda [16]		✓	✓		✓			✓	
Özdamar *et al.* [17]		✓	✓		✓			✓	
Tzeng *et al.* [18]		✓		✓		✓		✓	
Yi and Kumar [7]	✓		✓				✓	✓	
Yi and Özdamar [8]	✓		✓			✓		✓	
Kondaveti and Ganz [19]	✓		✓					✓	
Mete and Zabinsky [20]	✓		✓		✓			✓	
Sheu [21]	✓			✓				✓	
Lin *et al.* [22]		✓		✓			✓	✓	
Nolz *et al.* [23]		✓		✓		✓		✓	
Özdamar [9]	✓		✓					✓	
Afshar and Haghani [24]	✓		✓		✓			✓	
Berkoune *et al.* [25]	✓		✓					✓	
Zhang *et al.* [27]	✓						✓	✓	
Barzinpour and Esmaeili [28]				✓				✓	
Ahmadi *et al.* [29]				✓				✓	
Huang *et al.* [30]				✓				✓	
Rezaei-Malek *et al.* [31]		✓		✓	✓			✓	
Tofighi *et al.* [32]		✓		✓			✓	✓	
Zokaee *et al.* [33]		✓		✓	✓			✓	
Fahimnia *et al.* [34]	✓			✓				✓	
Mohamadi and Yaghoubi [35]		✓		✓	✓			✓	
Cao *et al.* [36]				✓				✓	
Samani *et al.* [37]		✓		✓	✓			✓	
Nikoo *et al.* [38]	✓			✓	✓			✓	
This paper	✓			✓	✓		✓		✓

Table 2. Model parameters for ten regions and three warehouses.

Regions	Demand of each regions	travel time between regions and warehouses			Travel time between each region									
		W_1	W_2	W_3	R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8	R_9	R_{10}
R_1	31992	35	113	185	-	173	141	116	182	150	138	170	175	258
R_2	85715	15	80	140		-	78	104	152	105	93	126	130	228
R_3	38406	40	30	62			-	29	77	27	15	48	52	153
R_4	45266	95	32	73				-	71	38	26	59	63	147

R_5	44489	187	80	121					-	86	74	106	111	77
R_6	28495	123	30	42						-	17	27	32	162
R_7	574415	132	18	32							-	38	42	150
R_8	87261	174	51	18								-	8	182
R_9	85715	189	55	15									-	187
R_{10}	15068	273	156	197										-

Table 3. Three levels of each parameter considered in the orthogonal experiment.

Algorithm	Parameter	Range	Level 1	Level 2	Level 3
NSGA-II	Population size (PS)	100 - 200	100	150	200
	Number of iteration (NOI)	300 - 600	300	450	600
	Mutation rate (MR)	0.02 - 0.1	0.02	0.06	0.1
	Crossover rate (CR)	0.5 - 0.9	0.3	0.6	0.9
MOPSO	Population size (PS)	100 - 200	100	150	200
	Number of iteration (NOI)	300 - 600	300	450	600
	Repository size (RS)	50 - 150	50	100	150
	Leader selection pressure (LSP)	1 - 2	1	1.5	2

Table 4. Calibration process of NSGA-II and MOPSO algorithms.

Runs	NSGAII						MOPSO					
	PS	NOI	MR	CR	OF	MOFV*	PS	NOI	RS	LSP	OF	MOFV
1	100	300	0.02	0.3	Z_1	0.785	100	300	50	1	Z_1	0.485
					Z_2	16.110					Z_2	21.692
2	100	450	0.06	0.6	Z_1	0.768	100	450	100	1.5	Z_1	0.515
					Z_2	15.360					Z_2	24.144
3	100	600	0.10	0.9	Z_1	0.767	100	600	150	2	Z_1	0.623
					Z_2	14.237					Z_2	28.131
4	150	300	0.06	0.9	Z_1	0.759	150	300	100	2	Z_1	0.625
					Z_2	17.505					Z_2	38.340
5	150	450	0.10	0.3	Z_1	0.790	150	450	150	1	Z_1	0.632
					Z_2	16.127					Z_2	31.383
6	150	600	0.02	0.6	Z_1	0.814	150	600	50	1.5	Z_1	0.617
					Z_2	13.680					Z_2	23.908
7	200	300	0.10	0.6	Z_1	0.759	200	300	150	1.5	Z_1	0.419
					Z_2	15.233					Z_2	26.381
8	200	450	0.02	0.9	Z_1	0.795	200	450	50	2	Z_1	0.475
					Z_2	11.977					Z_2	22.060
9	200	600	0.06	0.3	Z_1	0.763	200	600	100	1	Z_1	0.440
					Z_2	14.858					Z_2	21.168

* MOFV: Mean Objective Function Values.

Table 5. Optimal values of the parameters in NSGA-II and MOPSO algorithms.

Algorithm	Parameter	Optimal value
NSGA-II	Population size (PS)	200
	Number of iteration (NOI)	600
	Mutation rate (MR)	0.02
	Crossover rate (CR)	0.9
MOPSO	Population size (PS)	200
	Number of iteration (NOI)	600
	Repository size (RS)	50
	Leader selection pressure (LSP)	1.5

Table 6. Responses for S/N ratios in NSGA-II taking into account that smaller is a better state.

Level	PS	NOI	MR	CR
1	-30.19	-30.76	-29.36	-30.45
2	-30.46	-29.69	-30.55	-29.91
3	-29.43	-29.62	-30.17	-29.71
Delta	1.02	1.14	1.20	0.74
Rank	3	2	1	4

Table 7. Responses for S/N ratios in MOPSO taking into account that smaller is a better state.

Level	PS	NOI	RS	LSP
1	-34.32	-35.38	-33.59	-34.30
2	-36.24	-34.71	-35.19	-34.30
3	-33.78	-34.25	-35.55	-35.73
Delta	2.46	1.13	1.95	1.42
Rank	1	4	2	3

Table 8. Experimental results of ten runs for NSGA-II and MOPSO algorithms.

Runs	**NSGAII**					**MOPSO**				
	Δ	**IGD**	**NPS**	**CPU (second)**	**TOPSIS Index**	**Δ**	**IGD**	**NPS**	**CPU (second)**	**TOPSIS Index**
1	1.7292	1.019	45	1329	0.676	1.1673	10.127	14	1020	0.651
2	0.6514	1.952	39	1245	0.708	1.1694	9.954	15	1011	0.650
3	0.3917	3.872	34	1419	0.481	1.9913	9.53	12	1041	0.146
4	0.7895	4.254	34	1303	0.396	1.8512	10.823	13	1025	0.232
5	1.4633	0.169	39	1222	0.772	1.9725	11.842	12	1060	0.157
6	1.3265	0.564	41	1259	0.779	1.9558	9.956	14	1022	0.168
7	0.6830	5.523	37	1254	0.323	1.087	9.779	15	1063	0.701
8	0.5412	3.245	39	1210	0.538	1.9465	10.012	13	1059	0.174
9	1.8654	4.027	38	1269	0.273	2.2288	10.319	14	1060	0.019
10	2.3643	2.756	41	1357	0.411	0.5987	9.086	15	1066	0.976
Avg	1.180	2.738	39.1	1286.7	-	1.596	10.14	13.3	1042.7	-
Std	0.665	1.768	3.604	65.369	-	0.541	0.689	1.337	21.302	-

Table 9. ANOVA for performance metric Δ .

Source	DF	SS	MS	F-Value	P-Value
MOEA	1	0.8665	0.8665	2.36	0.142
Error	18	6.6194	0.3677		
Total	19	7.4859			

Table 10. ANOVA for performance metric IGD.

Source	DF	SS	MS	F-Value	P-Value
MOEA	1	274.15	274.148	148.40	0.010
Error	18	33.25	1.847		
Total	19	307.40			

Table 11. ANOVA for performance metric NPS.

Source	DF	SS	MS	F-Value	P-Value
MOEA	1	3328.2	3328.20	450.43	0.015
Error	18	133.0	7.39		
Total	19	3461.2			

Table 12. ANOVA for performance metric CPU time.

Source	DF	SS	MS	F-Value	P-Value
MOEA	1	297680	297680	125.95	0.020
Error	18	42542	2363		
Total	19	340222			

Table 13. Trade-off between two objective functions with different weight values.

w	Z_1	Z_2	CPU time (second)
0.1	0.9298	1.1952	122
0.15	0.8899	1.8622	134
0.2	0.8706	3.6031	136
0.25	0.8651	3.6514	125
0.3	0.8501	4.8849	129
0.35	0.8414	6.1101	139
0.4	0.7949	7.4366	124
0.45	0.6886	11.6427	136
0.5	0.6611	14.5378	137
0.55	0.6322	25.4773	126
0.6	0.625	31.6184	134
0.65	0.6308	40.7974	126
0.7	0.6254	45.9313	141
0.75	0.6228	46.9725	128
0.8	0.6198	47.1261	132
0.85	0.6094	47.954	127
0.9	0.6001	48.72	135

Table 14. Nine possible cases for changing vehicle allocations and adding new vehicles to the warehouses.

Warehouse	Current number of vehicles	Current allocation (in total 17 vehicles)			Adding 1 vehicle (in total 18 vehicles)			Adding 2 vehicle (in total 19 vehicles)		
		S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8	S_9
W_1	5	4	4	3	5	5	4	5	5	5
W_2	6	7	6	7	6	7	7	7	8	6
W_3	6	6	7	7	7	6	7	7	6	8

Table 15. Travel time between the candidate warehouses locations and earthquake-affected areas.

Candidate warehouse location	Travel time between candidate warehouse location and each area									
	R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8	R_9	R_{10}
W_4^1	153	150	45	72	93	15	27	15	23	135
W_4^2	127	135	57	51	20	27	15	42	37	49
W_4^3	210	195	163	89	17	99	43	180	68	20

Table 16. Nine possible cases for adding a new warehouse.

Warehouse	Vehicle allocations for W_4^1			Vehicle allocations for W_4^2			Vehicle allocations for W_4^3		
	S_{10}	S_{11}	S_{12}	S_{13}	S_{14}	S_{15}	S_{16}	S_{17}	S_{18}
W_1	4	4	4	4	4	4	4	4	4
W_2	5	6	5	5	6	5	5	6	5
W_3	6	6	5	6	6	5	6	6	5
W_4^1	5	4	6	-	-	-	-	-	-
W_4^2	-	-	-	5	4	6	-	-	-
W_4^3	-	-	-	-	-	-	5	4	6

AUTHORS STATEMENT

Mahmood Shafiee: Conceptualization, Methodology, Software, Validation, Formal Analysis, Investigation, Writing - Review & Editing, Visualization, Supervision.
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Mohsen Afsahi: Conceptualization, Methodology, Software, Validation, Formal Analysis, Investigation, Data curation, Writing - Original Draft, Visualization, Project administration.
Michael Patriksson: Methodology, Validation, Writing - Review & Editing.

RESEARCH HIGHLIGHTS

- A bi-objective non-linear optimization model for fuel distribution in post-earthquakes;
- Minimizing the penalties due to unsatisfied and/or lost fuel demands;
- Minimizing the difference between satisfied demands in different affected areas;
- Developing NSGA-II and MOPSO algorithms to solve the model;
- A Taguchi's design and experiment method to tune the algorithms' parameters;
- A real case study to demonstrate the applicability of the proposed framework.