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A stochastic multi-objective model based on the classical optimal search model for searching for the people who are lost in response stage of earthquake

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Abstract. Although after an earthquake, the injured person should be equipped with food, shelter, and hygiene activities, before anything must be searched and rescued. However, Disaster Management (DM) has focused heavily on emergency logistics and developing an effective strategy for search operations has been largely ignored. In this study, we suggest a stochastic multi-objective optimization model to allocate resource and time for searching the individuals who are trapped in disaster regions. Since in disaster conditions, the majority of information is uncertain, our model assumes ambiguity for the locations where the missing people may exist. Fortunately, the suggested model fits nicely into the structure of the classical optimal search model as it uses a stochastic dynamic programming approach to solving this problem. On the other hand, through a computational experiment, we observed that the model needed heavy computation. Therefore, we reformulated the suggested search model for a Multi-Criteria Decision Making (MCDM) problem and employed two efficient MCDM techniques, namely TOPSIS and COPRAS, to tackle the ranking problem. Consequently, the computational effort significantly decreased and a promising solution was achieved.

1. Introduction

In recent decades, increasing rates of the amounts of natural catastrophes, people affected, and the economic damages have been reported [1]. For example, during the 1960s and 1970s, more than 3,000,000 people were killed in natural disasters [2] and over 230 billion USD of the world wealth was eradicated [3]. Also, since the 1980s, the rate and impact of disasters have terribly increased (as shown in Figure 1). We refer the readers to the website of EM-DAT (EM-DAT is a famous database of natural and technological disasters) for valuable statistics about disasters from 1900 up to now.

According to World Health Organization (WHO) available at: URL: http://www.who.int/topics/en/ (accessed 2016 August), a disaster (There is difference between terms "disaster" and "catastrophe". But in this study these terms are employed interchangeably.) is a dire trouble in the normal operation of a community whose effects exceed the capability of community to control the conditions. As pointed out in EM-DAT, between 2000 and 2010, around 8400 disasters happened in the world, i.e., more than two catastrophes every day. According to WHO, 3.4 billion dwell in regions where at least one natural disaster may terribly shock them. For example, Iran is one of the most

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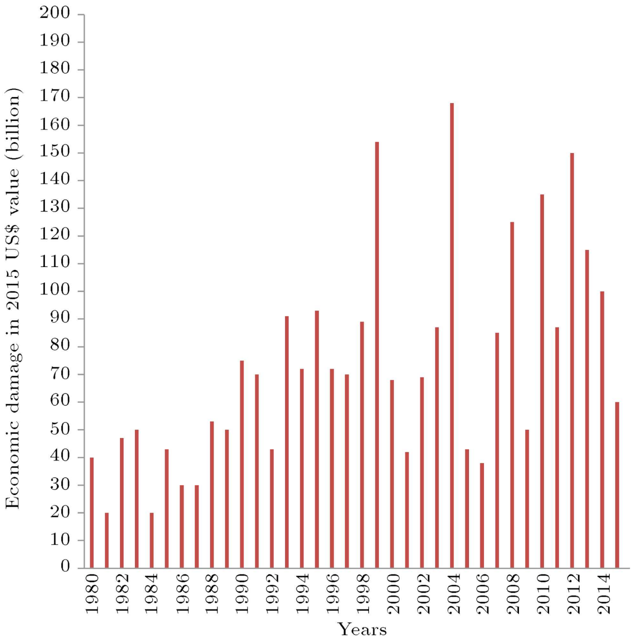

Figure 1. The reported annual economic damages and time trend of disasters: 1980-2015 derived from United Nations Office for Disaster Risk Reduction (http://www.unisdr.org/we/inform/publications/47804).

disaster-prone countries and has the 10th rank in this regard in the world. This country has experienced 31 out of 40 forms of natural disasters and these catastrophes have destroyed 232 million USD of the wealth of this country in the last decade [4].

In 20th century, earthquakes killed more than 1,500,000 people around the world [5]. According to [6], two earthquakes occur in the world every minute and, as pointed out by United Nations (UN), millions of people are in danger of earthquakes. For example, over 90% of Iran is built on fault lines. Also, Iran is one of the top ten in terms of the rate of earthquakes. Considering the number of victims of earthquake, Iran is number one (United Nations, Living with risk: a global review of disaster reduction initiatives, (2004)). Tehran, the capital of Iran, is created above several faults and the likelihood of the occurrence of a very intense earthquake ($Mw > 7$) is approximately 70% [7].

On the other hand, it is believed that Global Warming will speed up the number of natural calamity shocks [8]. Lay [9] warned that between 2004 and 2014, approximately 1.8 great earthquakes per year happened globally, compared to 0.68 earthquakes per year from 1900 to 2004. These numbers show a terrifying increase by 265%. Furthermore, Singh [10] pointed out that the world population would increase from 7 billion in 2011 to 9.30 billion in 2050. Accordingly, due to the unbridled growth of the population as well as the global urbanization, the threat of earthquake will increase [5].

As pointed out by Hou and Shi [11], destruction of an earthquake is not straight determined by its magnitude. For example, from 1980 to 2002, India experienced 14 earthquakes with 32,117 killed while the United States experienced 18 earthquakes with 143 killed [8]. On the basis of the formula of risk, namely $Risk = Hazard \times (Vulnerability - Resources)$, efficient distribution of resources will reduce the likelihood of damage considerably. According to [12], DM (or emergency management) refers to a group of actions done before, during, and after a catastrophe with the aim of preventing loss of people, diminishing the disaster shock, and coming back earlier to normal conditions. Often, DM is divided into four key steps as shown in Figure 2. Mitigation is the various activities taken to lessen the possibility of catastrophe occurring

Figure 2. Disaster management cycle and some classic activities.

or to decrease its destructive shocks. Preparedness organizes the society to respond when a calamity takes place. Response is the utilization of resources to protect life, assets, the milieu, and the political organization of the society. Recovery is the long-term designs to revert to normality [12].

Obviously, in the early hours after a disaster, the response step must concentrate on search and rescue (SAR). SAR activities are utilized to track people after a dreadful catastrophe and when individuals are lost [13]. As mentioned, in all SAR activities, time is one of the most vital factors. According to [14], numerous human beings trapped under the debris in the earthquake may have a great chance to remain alive if they are saved in the golden time, i.e., 72 h after quake. Chang and Nojima [15] pointed out that 24 h after quake would be the golden rescue phase. According to Chen and Miller-Hooks [16], between the first day and fifth day after the 1976 Tangshan earthquake, the survival rate decreases from 81% to 7.4%. Fiedrich et al. [17] suggested a dynamic frame to approximate such a rate as shown in Figure 3. Based on this model, the first 72 h are the most serious for rescuing. Obviously, SAR operations take massive amounts of money and time. As a result, in disaster situation, decision makers must utilize finite resources and limited time efficiently to attain the best relief. However, one significant complexity of the response period is to find the best strategy for assignment of time and resource to SAR operations. In addition, due to the constraints on time and resources, any strategy to support search operations contains some aspects of uncertainty (e.g., the number of missing persons or the probable locations of them after disaster). Thus, utilizing a practical and efficacious approach to importing this stochastic nature into the decision-making procedure is very vital.

Search for individuals lost in disaster fits into the framework of the Search Theory (ST). ST is the study of how to efficiently use restricted resources when attempting to detect a goal whose position is not exactly known [18]. ST is one of the oldest parts of Operations Research (OR) [19]; however, by analyzing the literature, severe scarcity of a search strategy on the basis of OR techniques in DM is revealed. It is noteworthy that because the majority of researchers have focused deeply on emergency logistics, more specifically on two main problems, namely location and transportation [20], developing various effective strategies for search operations has been largely ignored. To reduce this gap, our study focuses on the problem of optimal distribution of time and resources to discover an objective, namely missing people. Fortunately, the search problem for missing people fits nicely into the structure of the Classical Optimal Search Model (COSM). Generally, in this model, a single motionless goal (In this study, the terms "aim", "target", and "goal" are employed interchangeably.) is in one of the given locations. The search consists of a series of discrete investigations until the aim is detected. Looking into location, i, costs C_i, and p_i is the probability that the goal is in the location i. The aim is to find out the goal at minimum expected cost [21,22]. Among the various measures of efficiency that are employed in ST, the most common factors are expected time for discovery, expected cost of discovery, and probability of discovery. From a mathematical point of view, this problem has been broadly tackled by Dynamic Programming (DP) method. DP, which was introduced by Bellman and Dreyfus [23], is a valuable method to handle multi-step decision processes [24,25]. On the other hand, multi-objectivity is one of the most significant attributes of real-world problems. Generally, decision-making in today's world needs various compromises among several conflicting goals. In view of the inherent restrictions on resources and time, the problem of search has a multi-objective frame. Consequently, a multi-objective search model in stochastic environment can appropriately satisfy the necessities of this problem in the real world.

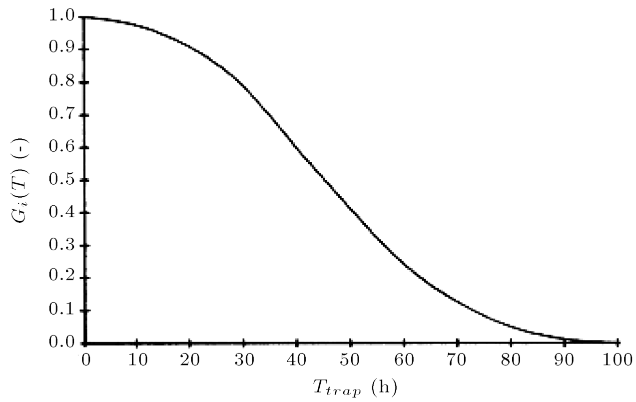

Figure 3. Expected survival rate according to the model of Fiedrich et al. [17].

The aim of this study is to introduce a stochastic multi-objective model based on COSM for SAR of trapped people immediately after an earthquake. To find a solution to this Multi-Objective Problem (MOP), we employ Compromise Programming (CP). CP, which is one of the most accepted techniques for coping with the MOP, provides a robust solution which belongs to the Pareto set. According to Gutjahr and Nolz [26], who reviewed multicriteria optimization in humanitarian help, there are few studies (e.g., [27]) adopting CP in DM field. However, various stochastic problems modeled by DP usually suffer from the "dimensionality" concept, which leads to a huge increase in the computational efforts as well as required memory when the dimension of the state grows [28]. Thus, it is essential to point out that many MOPs on the basis of DP are close to unfeasible to optimize for a practically sized

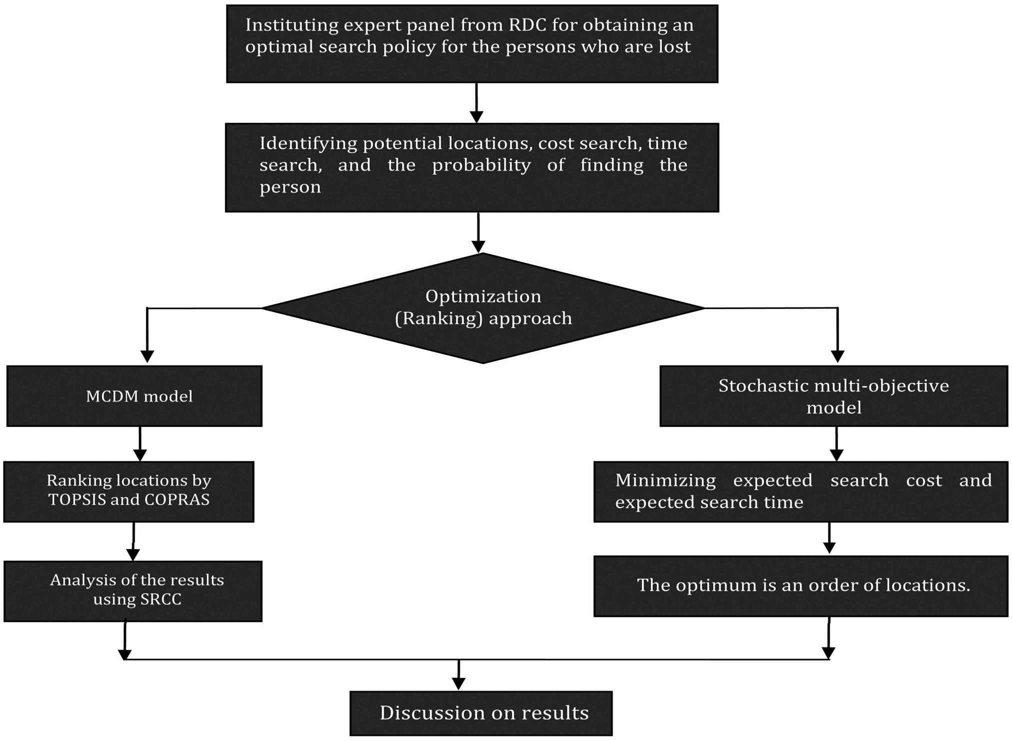

Figure 4. The proposed decision framework for the search problem.

problem. Fortunately, as pointed out by Garey and Johnson [29], optimization does not essentially mean obtaining the (global) optimum solution to a problem, because it may be impracticable due to the structure of problem in some cases. Because using multi-objective stochastic dynamic programming approach to handling decision making problems is often very difficult, in this paper, as an alternative solution, an MCDM framework is adopted for the search problem. It is noteworthy that in the real cases, in which the exact technique needs a long calculation time, MCDM methods act as an approximate approach. The suggested decision framework in this paper is depicted in Figure 4.

The remainder of this work is arranged as follows. In Section 2, the related literature is briefly reviewed. We discuss the classical optimal search model and multi-objective optimization problem in Section 3, leading to the suggested method in Section 4. The efficiency of our model is analyzed by a case study in Section 5. Section 6 provides an alternative framework based on MCDM for the search problem. In Section 7, we finish this work with conclusion and future study guidelines.

2. Literature review

Clearly, during the past 10 years, the papers related to logistics of the response period have greatly been expanded. For example, Afshar and Haghani [30] suggested a comprehensive mathematical framework to control the flow of various supplies in the response system. Berkoune et al. [31] considered a compound transportation problem, namely multi-vehicle, multi-depot, and multi-product, for the transportation of humanitarian help. Najafi et al. [32] focused on a stochastic multi-objective, multi-commodity, multi-mode, and multi-period framework to tackle the problem of providing logistics for injured persons as well as supplies after earthquake. Bozorgi-Amiri et al. [27] developed a multi-objective robust stochastic approach to disaster relief logistics. Abounacer et al. [20] suggested a multi-objective location-transportation framework and proposed an ε-constraint technique to tackle it for disaster response. Bozorgi-Amiri and Asvadi [33] concentrated on selecting optimum sites for relief logistic hubs. Sheu [34] focused on a relief allocation problem in the critical rescue stage. Ma et al. [35] provided a robust transportation framework to minimize the maximum time of rescue for wounded persons.

Altay and Green [12] prepared a significant review of the application of OR approach to DM until 2004. Also, Galindo and Batta [36] presented a valuable study as a continuation of the study by Altay and Green [12]. According to these studies, although DM is a dynamic branch in OR, some gaps can be perceived. However, we observed only one article related to the problem of search in the reviewed literature, namely the study by Jotshi and Batta [37]. They suggested a heuristic to resolve the search problem for a stationary goal on a network [37]. Before that, Fiedrich et al. [17] introduced a dynamic optimization model with the aim of minimizing the number of victims in the period of SAR. Chen and Miller-Hooks [16] formulated the problem of optimally positioning SAR teams as a multistage stochastic program. The object of this model was to maximize the expected quantity of rescued persons. Berger and Lo [38] proposed a mixed-integer linear framework to optimally handle the multi-agent discrete SAR path problem. Briefly, by analyzing the literature, especially four comprehensive reviews in [12,36,39,40], we can see that the search problems have not been as emphasized as location and transportation problems in DM.

Search for persons who are lost after earthquake falls under the realm of ST. The first developments to ST were proposed by Koopman [41] in World War II to prepare efficacious techniques of finding submarines. Although surprisingly ST and related problems have vanished for more than twenty years [42], several problems such as searching for a hidden mine land [43], hidden hostage, and explosive material emphasize the need for effective search strategies for detecting targets of different forms [40]. As pointed out by [44], because of its stochastic structure and the nonlinearity due to the probability of finding, the problem of obtaining the "best" policy for search is basically very difficult. Several valuable studies on ST as well as search problems have been presented [19,22,45,46]. A number of parameters in which search scenarios vary are as follows [38,45]:

1. One-Sided (OS) search in which the goal does not react to the act of searcher. In this theme, the most tangible measure of efficiency for the search process is the expected cost or the expected time of the search. Black [21], Stone [19], and Washburn [46] concentrated on the OS search framework for the first time. Also, OS search can be clarified by various attributes such as:
    - 1.1. Discrete Search Problem (DSP) (e.g., [42]) versus Continuous Search Problem (CSP) (e.g., [47]);
    - 1.2. Stationary goal search (e.g., [21]) versus moving goal search;
    - 1.3. Multiple goals search (e.g., [47]) versus single goal search [22].
2. Two-Sided (TS) search in which the objective reacts to the act of searcher (search games).

Also, constrained searcher motion is another model which develops in search problem. In this type, some constraints on the motion of searcher are considered. As pointed out by Trummel and Weisinger [48], this category of search problem is NP-hard. A very good survey of search games was provided in [49]. Also, Chudnovsky and Chudnovsky [50] presented a review of OS search as well as TS search. Moreover, a survey of pursuit-evasion game in mobile robotics was conducted by Chung et al. [51]. Figure 5 depicts a general categorization of search parameters.

After presenting the classic model by Black [21], diverse models of DSPs have been developed. For example, Chew [52] analyzed this problem for maximizing the probability of detection the target under cost restraints. Ross [53] extended the outcome of the study of Chew [52]. He assumed that in the new model, a prize R_i was earned if the goal was detected in the location i. Smith and Kimeldorf [54] suggested a DSP with an unknown number of objectives. The goal of this work was to minimize the expected cost in discovering at least one goal. Assaf and Zamir [47] focused on a DSP when there was over one immobile concealed target. Wegener [55] proved that the general search problem (switching cost problem) with the minimum expected time and cost of switches was NP-hard. Kadane [56] proposed a search strategy that maximized the detection probability of the target considering a restraint on the existing budget.

Various optimization techniques are being employed for solving search problems. Zahl [57] employed Lagrange Multiplier (LM) to tackle a search problem. Kadane [58] developed a branch and bound approach to dealing with some limitations in the LM method for a discrete instance. But, due to sequential nature of the optimal search model as well as substitute decisions of this optimization frame, Ross [22] utilized DP approach to coping with this model. In contrast to several other techniques such as LM, DP puts no constraint on the non-convex structure of different problems and provides the global solution. In addition, this technique is capable to model sequential decision systems and non-linear structures [42]. However, DP is usually not easy to apply. Further information on DP and applications can be obtained in several well-known books, e.g., [23].

On the other hand, ambiguity has stimulated numerous researchers to address stochastic optimization in disaster response procedures. Mathematically, Stochastic Programming (SP) is a framework in which the ambiguities are depicted as random variables with identified probability functions. However, SP techniques are generally avoided because they increase the intricacy of problems. A good survey of SP was provided by Gutjahr and Pichler [59].

The term "Stochastic Dynamic Programming" (SDP) was first utilized by Prof. Richard Bellman. SDP differs from deterministic DP in that the state at the following period is not absolutely specified by the state and decision at the present period. For what the following state will be, we use a probability distribution [60]. Cervellera et al. [28] proposed an optimization model for a large-scale water reservoir

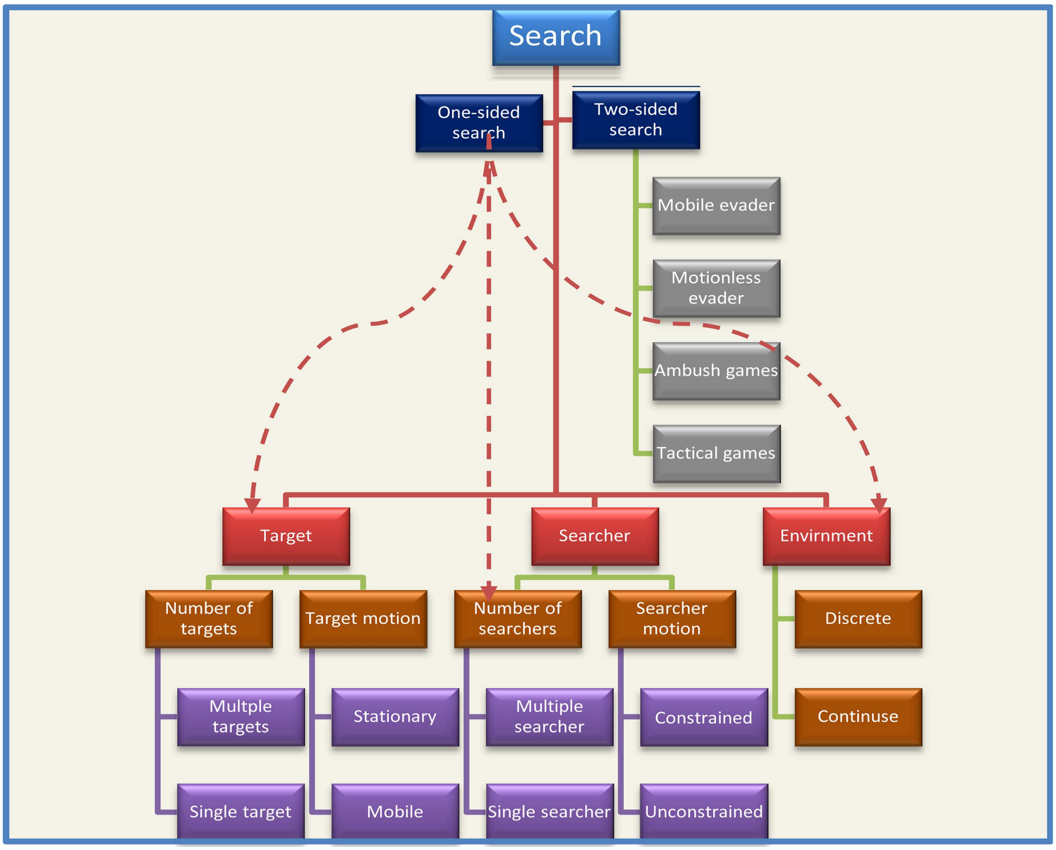

Figure 5. General categorization of search parameters.

system using SDP. Li et al. [60] developed an uncertain production planning based on SDP. Ross [22] utilized SDP for solving the search problem. However, Marescot et al. [61] pointed out that, despite the growing number of the usages of this technique in different problems, SDP still suffered from a general incomprehension.

Multi-objectivity is a fundamental aspect of engineering optimization, especially DM. Gutjahr and Nolz [26] presented a comprehensive literature review of the application of this form of optimization to DM. Although real-life problems almost always have multi-objective as well as stochastic nature, these branches, namely stochastic optimization and MOP, flourished individually and separately from each other [59]. Hoyos et al. [40] reviewed the literature on DM based on OR methods with stochastic elements. In this review, some studies about facility location, resource allocation, relief distribution, and evacuation can be found. But few, if any, have attempted to present a study about the search issue in DM. There are only two studies about SAR, namely [16] and [37]. Although before them, Richardson and Discenza [62] discussed the utilization of ST in the SAR actions of the U.S. Coast Guard, none of these articles helps directly to solve the problem of search generally.

Finally, to the best of our knowledge, developing a multi-objective stochastic frame for search in DM literature is completely novel.

3. Preliminaries

In this part, a number of basic models and methods are reviewed.

3.1. The classical optimal search model [22]

As mentioned by Chew [52], a class of optimization problems, called searching problems, is concerned with a procedure which provides optimal value instead of the value itself. Of this nature, we review classical optimal search model [52] as follows:

An immobile objective is in one of the n locations where $n(\in \mathbb{N})$ is known ($\mathbb{N}$ is the natural number set). For each location i, P_i is the probability that the goal is in the location i, where $\sum_{i=1}^{n} P_i = 1$ and the cost for every glance in the location i is C_i. The probability that an objective in the location i will be discovered at a single glance is α_i and, as a result, the probability of failing to see the objective for location i is $1-\alpha_i$. The aim of this model is to detect the goal at minimum expected cost; therefore, it is a cost-oriented search model. This process finishes when the goal is detected. Clearly, the plan for search is a procedure which determines the search order. As mentioned by

Ross [22], this model has a decision procedure whose state is the posterior probability $P = (P_1, ..., P_n)$, with P_i indicating the posterior probability, given all that has happened and that the target is in region i. Mathematically, $V(P)$ is minimum expected cost equation and can be defined as follows:

$$V(P) = \min_i \left[C_i + (1 - \alpha_i P_i) \times V(T_i(P))\right]. \qquad (1)$$

In the above equation:

$$T_i(P) = \left[(T_i(P))_1, ..., (T_i(P))_n\right]$$

is the posterior probabilities given the previous probability P and given that an inspection of region i was useless. Hence,

$$(T_i(P))_j = P(\text{in } j \,|\text{search of } i \text{ unsuccessful})$$

$$= \begin{cases} \frac{P_j}{1-\alpha_i P_i}, & i \neq j \\ \frac{P_j(1-\alpha_i)}{1-\alpha_i P_i}, & i = j \end{cases} \qquad (2)$$

For a certain state P, a strategy can be considered as an order of regions with the explanation that the regions are sought in that arrangement until the target is discovered.

Lemma 3.1

Suppose that $V_\delta(P)$ indicates expected cost equation under δ. Also, assume that (i, j, δ) represents the strategy that first seeks i, then j, and at last δ. For any strategy δ, we have $V_{(i,j,\delta)}(P) \leq V_{(j,i,\delta)}(P) \Leftrightarrow \frac{\alpha_i P_i}{C_i} \geq \frac{\alpha_j P_j}{C_j}$.

Proof: Assume $i \neq j$. Subsequently, we have:

$$V_{(i,j,\delta)}(P) = C_i + (1 - \alpha_i P_i)\Bigg[C_j + \left(1 - \frac{\alpha_j P_j}{1 - \alpha_i P_i}\right) V_\delta(T_j T_i P)\Bigg] = C_i + C_j, + V_\delta(T_j T_i P) - \alpha_i P_i V_\delta(T_j T_i P) + \alpha_j P_j V_\delta(T_j T_i P) - \alpha_i P_i C_j, \qquad (3)$$

$$V_{(j,i,\delta)}(P) = C_j + (1 - \alpha_j P_j)\Bigg[C_i + \left(1 - \frac{\alpha_i P_i}{1 - \alpha_j P_j}\right) V_\delta(T_i T_j P)\Bigg] = C_i + C_j + V_\delta(T_i T_j P) - \alpha_i P_i V_\delta(T_j T_i P) + \alpha_j P_j V_\delta(T_j T_i P) - \alpha_j P_j C_i. \qquad (4)$$

We know that $T_j T_i P = T_i T_j P$ and $\alpha_i P_i C_j \geq \alpha_j P_j C_i$; thus, this completes the proof.

Proposition 3.1

In the above model, the best strategy is to seek a region with the largest value of $\frac{\alpha_i P_i}{C_i}$ $i = 1, 2, ..., n$. In other words, the maximum value of $\frac{\alpha_i P_i}{C_i}$ minimizes the expected cost to detect.

Proof: Assume that $\frac{\alpha_1 P_1}{C_1} = \max \frac{\alpha_i P_i}{C_i}$. Now, think about a strategy such as δ that does not seek location 1 at first. This strategy searches location 1 at time j, namely $\delta = (i_1, ..., i_{j-1}, 1, i_{j+1}, ...)$. By Lemma 3.1., clearly, a superior policy is acquired by swapping 1 and i_{j-1}, i.e., $\delta' = (i_1, ..., 1, i_{j-1}, i_{j+1}, ...)$ is superior to δ. By iterating this reasoning, we can see that $(1, i_1, ..., i_{j-1}, i_{j+1}, ...)$ is superior to δ. Consequently, for every policy not at first searching 1, we can obtain a better strategy that does start with 1.

3.2. Multi-objective optimization problems

In this sub-section, some definitions and famous algorithms for multi-objective optimization problem (known as multi-objective problem in this work), using [20,26,63-66] have been summarized.

Real problems are often multi-objective and the objectives disagree with each other in them. Therefore, nearly all decisions need trade-offs among various non-commensurable and incompatible objectives. MOP is more rational than a Single-objective Optimization Problem (SOP) in terms of real applications. It can be formulated in a minimization case as follows:

$$\begin{cases} \min & f(x) = (f_1(x), f_2(x), ..., f_m(x)) \\ s.t. & x \in D \end{cases} \qquad (5)$$

In the above frame, $m(\geq 2)$ is the number of objectives, $x = (x_1, x_2, ..., x_n)$ is the vector of variables, and D is the solution space. A MOP often does not have one optimum, but a group of solutions recognized as the Pareto-optimal set. First of all, some basic definitions in MOP are reviewed. In a minimization form, these notions are clarified as follows [20]:

- **Definition 1.** Pareto dominance: A vector $u \in D$ dominates a vector $\nu \in D$ in the Pareto logic if:

$$\begin{cases} f_i(u) \leq f_i(v) & \text{for all } i \in \{1, ..., m\} \\ f_j(u) < f_j(v) & \text{for at least one } j \in \{1, ..., m\} \end{cases}$$

- **Definition 2.** Pareto optimal solution (non-dominated solution or efficient solution): A solution $u \in D$ is a Pareto-optimal solution if there is no $\nu \in D$ such that ν dominates u.
- **Definition 3.** Pareto optimal set: The Pareto optimal set is specified as $P = \{x \in D : x \text{ is a Pareto optimal solution in } D\}$.

- **Definition 4.** Pareto front: The Pareto front is specified as $P\mathbb{F} = \{f(x) : x \in P\}$, where P is the Pareto optimal set.

More formally, a solution is in the Pareto set if no amelioration is achievable in an objective function without deterioration in another objective function. As mentioned earlier, there are various techniques to cope with MOP. One of the most common methods for MOP is using scalarizing techniques (classical approaches). Scalarizing techniques reduce the MOP into a SOP and optimize the SOP. Obviously, these techniques facilitate the computational effort of MOPs. The Weighted-Sum (WS) and the ε-constrained are among the most widespread techniques of this group. Although the ε-constrained technique has a number of benefits over the WS method, each of these techniques has various shortcomings. For example, WS technique is not capable to acquire non-dominated solution in a non-convex Pareto front. Also, this technique cannot suitably estimate the Pareto-optimum curve [66,67]. On the other hand, ε-constrained technique is not suitable for a problem with several objective functions.

The CP is a reputable mathematical programming which works efficiently for MOPs. CP belongs to a group of MOP techniques called "distance-based" approaches, which seek the closest solution to the reference point (ideal solution) considering a distance index. The outstanding advantage of CP is its very straightforward framework. The CP techniques vary in their selections of the distance metric as well as the reference point. The most common option as a reference point is the ideal point that is optimum for every objective function separately in a MOP. The distance between a Pareto-optimum (to be searched) and the reference point can be computed by the L_p metric, which is defined as:

$$L_p = \left[\sum_{i=1}^{m} w_i({z_i}^* - z_i)^p\right]^{\frac{1}{p}}, \quad 1 \leq p \leq \infty. \tag{6}$$

In Model (6), m shows the number of objective functions, w_i is the weight of objective i (the L_p metric coefficient), z_i is non-dominated solution, z_i^* is the ideal solution, and p indicates the significance of the maximum deviation from the ideal solution. In other words, as p increases, the significance of the deviations escalates.

Going back to Model (6), because of the utilization of non-commensurable units in various objectives, normalization is necessary. We normalize Model (6) by the reference point [68] as follows:

$$L_p = \left\{\sum_{i=1}^{m} {w_i}^p \left[\frac{(z_i^* - z_i)}{{z_i}^*}\right]^p\right\}^{\frac{1}{p}}. \tag{7}$$

To tackle a MOP by CP, the L_p given in Model (7) is minimized. In other words, given p and w_i, the option with the minimum L_p will be the best since it is the nearest point to the ideal solution. It should be noted that when $1 \leq p < \infty$ and all weights are strictly positive, CP generates Pareto optimal solution [64]. Proofs have been provided in nearly all books about MOP.

4. The stochastic multi-objective search problem

This part explains the main problem of this paper and provides a mathematical form for it.

4.1. Problem description

Let us begin with notations and explanation of the objectives of the suggested framework. Table 1 demonstrates the notations.

Table 1. Notations.

n	Number of locations
$\mathbb{N}$	The natural number set
i	Index of locations $i = 1, 2, ..., n$
C_i	Search cost of location i
t_i	Search time of location i
α_i	Probability that a goal in location i will be discovered at a single glance
P	Posterior probability vector that the goal is in location i
$V(P)$	Expected cost function
$W(P)$	Expected time function
$T_i(P)$	Posterior probability vector considering prior probability vector and failure in discovering the target in location i
χ	Solution space
k	Number of possible scenarios
Z	The value of L_p-metrics function
w	L_p-metrics coefficient

Suppose that a motionless target is located in one of the locations. It is essential to point out that the number of locations is known and $n \in \mathbb{N}$. The precise location of the goal is unknown, but to the searcher, the probability that the goal is in that location is known. Also, we have $\sum_{i=1}^{n} P_i = 1$. The solution (search) space χ is discrete and search cost and search time of location i are C_i and t_i, respectively. The search problem is to obtain in what order the locations should be checked to minimize the expected cost and expected time of the search.

Avoiding unimportant cases, we suppose that none of the parameters C_i, t_i, and P_i is zero. Let us point out that although Ross [53] relaxed the condition $C_i > 0$ and analyzed this problem, in our suggested model, any $C_i = 0$ (or $t_i = 0$) is meaningless.

4.2. Solution procedure

Designing an applicable search procedure is a subset of resource distribution problem. After earthquake, resources for search are almost always inadequate. Thus, there is a need for experts to decide on how to apportion the resources among the various strategies in order to minimize the impact of the earthquake. Furthermore, the search plan in the response stage contains another goal. After the majority of earthquakes, lives of missing persons depend on minutes and the chance to discover survivors after golden time is tremendously low. Therefore, the decision maker aims to minimize the time for unserved missing persons.

With the above postulation, we concentrate on two objectives for the suggested model: to minimize expected search cost and to minimize expected search time.

On the basis of the aforementioned goals, we present the following stochastic multi-objective model for the search problem.

Two objectives are considered for the suggested search problem as follows:

1. *Expected search cost, which is the expected cost of search in the DM.* The first objective is to minimize the expected search cost. It is the mathematical expectation of search cost and takes the following model:

$$V(P) = \min_i \left[C_i + (1 - \alpha_i P_i) \times V(T_i(P))\right]. \quad (8)$$

The objective function $V(P)$ takes into account and minimizes the total cost of search operation, including the transportation cost, expert cost, etc.;

2. *Expected search time, which is the expected time of search in the DM.* Now, the second objective is to minimize the expected search time. It is the mathematical expectation of search time and takes the following model:

$$W(P) = \left[t_i + (1 - \alpha_i P_i) \times W(T_i(P))\right]. \quad (9)$$

The objective function $W(P)$ takes into account and minimizes the total time of search operation, including transportation time, deployment time, etc.

As a result, the stochastic multi-objective search problem will be formulated as follows:

Minimize

$$\begin{cases} \underbrace{V(P) = [C_i + (1 - \alpha_i P_i) \times V(T_i(P))]}_{\text{expected search cost function}} \\ \underbrace{W(P) = [t_i + (1 - \alpha_i P_i) \times W(T_i(P))]}_{\text{expected search time function}} \end{cases} \quad (10)$$

Two objectives are simultaneously minimized in the absence of certain restrictions. Therefore, a multi-objective technique is indispensable for handling the problem. After building our stochastic multi-objective framework by Model (10), CP is employed to tackle the suggested MOP for the search problem. For doing so, first, we solve the suggested MOP as two single-objective models, separately. Then, we reformulate our MOP as a SOP by a weighted aggregation. This SOP minimizes the sum of the differences between an objective and its optimum when each objective function is normalized. By recalling Model (7) for $p = 1$, the L_p-metrics function will be obtained as follows:

$$Z = \min \left[w \frac{V^*(P) - V(P)}{V^*(P)} + (1 - w) \frac{W^*(P) - W(P)}{W^*(P)}\right]. \quad (11)$$

According to Proposition 3.1, the policy which seeks a location with the largest value of $\frac{\alpha_i P_i}{C_i}$ minimizes the expected search cost in Model (8). Also, Sadi-Nezhad et al. [43], by using a similar approach, showed that the plan which searched a location with the largest value of $\frac{\alpha_i P_i}{t_i}$ could minimize the expected search time in Model (9). Now, we employ Model (11) with the identical relative weight of 0.5 to solve the proposed multi-objective search problem. Let us point out that when there are no preferences for the objectives, obtaining a group of Pareto optimal solutions to a MOP is challenging. In this problem, the decision maker is not willing to give the preference for an objective to another objective. For this reason, to highlight the significance of simultaneously considering the cost and time of search, we set w equal to 0.5 in Model (11). The reader is referred to [63] for a classification of MOP techniques on the basis of the role of the decision maker in a solution procedure. To obtain a desirable solution such that the expert can reach a compromise between cost and time on the basis of the results, Model (11) can be solved while changing the L_p-metrics coefficient several times. The solution will be one of the search scenarios (There is difference between terms "scenario" and "policy". But in this study, these terms are employed interchangeably.) which minimizes the above L_p-metrics function. As mentioned, χ is the set of possible solutions and solution space is any search sequence of the locations. Let us recall that the solution in the suggested problem is a procedure which provides optimal value instead of the value itself. Hence, we will have $k = n!$ possible scenarios. Clearly, the suggested model determines the best scenario for search process among the possible scenarios while trying to minimize search cost and search time. Thus, in the problem setting, a scenario-based approach is used to contain all discrete scenarios. It is noteworthy that scenario-based SP optimizes the expected value of the objectives without directly employing priorities of the expert [69]. In the scenario-based SP, a group of discrete policies and their related probabilities will be considered; but in this problem, we take into account all possible scenarios. Obviously, due to the scenario-based nature of the search problem, CP is better than other multi-objective methods in terms of calculation time. Now, in this step, we obtain all possible search scenarios as the solution space. In our problem, search scenario is any search sequence of the locations. In these sequences, each location will appear only once. For example, [location 1, location 3, location 4, location 2] or [location 4, location 1, location 2, location 3] is a feasible search scenario for the given four locations. Clearly, Model (11) is nearly impossible to handle directly. Hence, all possible scenarios are separately placed in Model (11). Finally, the scenario with the minimum Z will be the best. It is obvious that Model (11) is feasible as well as bounded. It is very straightforward to prove.

In the next section, we prepare a numerical example to elucidate the working of the proposed model.

5. Numerical example

In this section, to explain how the suggested model works, we analyze a realistic application.

5.1. Database formation

This case is derived from a real event after an earthquake. (Because of some social and political concerns, the name of the earthquake remains confidential.) At first, we asked an experienced expert in the field of DM to score the locations by using the experiences of the 1990 Manjil, the 2003 Bam, and the 2012 Ahar and Varzaghan earthquakes in Iran. This expert had more than 30 years of experience for various topics of DM in Iran and fortunately, he was familiar with the basic concepts of OR. Finally, the senior manager who verified those responses had above 20 years of experience in the relief activities.

5.2. Case study

After an earthquake, a search committee in the Relief Distribution Center (RDC) is organized to search and rescue a missing family. According to some evidences, they are probably trapped during the earthquake in one of the following locations: a cottage far from the city (location 1), a forest near the city (location 2), and a mountain near the city (location 3).

The probability that they are in each of the above locations is as follows (Table 2).

As explained, the family is in one of these locations. Thus, we have $\sum_{i=1}^{3} P_i = 1$. Due to the need for experts as well as special equipment, search is more expensive in the mountain than in other locations. Considering this fact, the search cost of each location is estimated as shown in Table 3.

Helicopter cannot land near the cottage. Thus, access to the cottage is possible only through a road. The distance between the cottage and RDC is more than 175 km. Therefore, due to the impossibility of using helicopter, road damage, and remoteness, more time will be spent on search in the cottage than in other locations. The search time of each location is estimated as shown in Table 4.

As mentioned by Chew [52], this class of optimization problems is concerned with a procedure which obtains optimal value instead of the value itself. Therefore, the key problem is how to select a policy to simultaneously minimize the expected cost and expected time of searching for the family.

Table 2. Probability of finding the goal.

Location	Probability (%)
Location 1 (cottage)	38
Location 2 (forest)	28
Location 3 (mountain)	34

Table 3. Search cost of each location.

Location	Search cost (thousand USD)
Location 1 (cottage)	23
Location 2 (forest)	25.5
Location 3 (mountain)	30

Table 4. Search time of each location.

Location	Search time (hour)
Location 1 (cottage)	19
Location 2 (forest)	17.5
Location 3 (mountain)	16

5.3. Solution

As mentioned, it is assumed that the family is in one of the 3 locations ($\sum_{i=1}^{3} P_i = 1$). On the other hand, each policy for searching for the family is a search order of locations. In this case, we have 3 locations. Therefore, there are 6 ($k = 3!$) possible scenarios for search. Suppose that [location 1, location 2, location 3] indicates that at the start, location 1 is searched; if the family is not detected, then location 2 is searched and if the family is not detected in location 2, then location 3 is searched. These three locations will be referred to as 1, 2, and 3 abbreviated as [1, 2, 3]. As mentioned, there are 6 possible policies for search as follows:

$$\{[1,2,3],[1,3,2],[2,1,3],[2,3,1],[3,1,2],[3,2,1]\}\in\chi.$$

For simplicity, we suppose that the probability that the family in location i will be discovered at a single glance is one. Thus, $\forall i, \alpha_i = 1$ that is, according to this scenario, firstly location i is searched; if the family is not detected, this location will not be considered anymore. Now, Model (11) is used to obtain the solution. However, the model is nearly impossible to solve directly. Therefore, all six possible scenarios are separately placed in Model (11) and the scenario with the minimum Z will be the best. The model has been coded by Python 3.3 for each strategy. Python has a very lucid syntax and provides the majority of the functionalities. Also, this interpreter is free. A comparison between Python and MATLAB (another high-level language) was presented by Fangohr [70]. It is noteworthy that our suggested model is carried out on a laptop with Intel Core i5, CPU 2.5 GHz, and 4GB RAM. Now, we calculate the value of Model (11) for each policy as follows.

First, by using Proposition 3.1, we obtain $\max \frac{\alpha_i P_i}{C_i}$ as well as $\max \frac{\alpha_i P_i}{t_i}$ for i = 1,2,3; considering the assumption of $\forall i, \alpha_i = 1$, we have:

$$\frac{P_1}{C_1} = \frac{0.38}{23} = 0.0165, \qquad \frac{P_2}{C_2} = \frac{0.28}{25.5} = 0.0109,$$

$$\frac{P_3}{C_3} = \frac{0.34}{30} = 0.0113$$

as well as:

$$\frac{P_1}{t_1} = \frac{0.38}{19} = 0.02, \qquad \frac{P_2}{t_2} = \frac{0.28}{17.5} = 0.016,$$

$$\frac{P_3}{t_3} = \frac{0.34}{16} = 0.0212.$$

Therefore, we consider all possible scenarios as follows:

- **Policy 1:** Model (11) for scenario [1, 2, 3] as shown in Box I.
- **Policy 2:** Model (11) for scenario [1, 3, 2] as shown in Box II.
- **Policy 3:** Model (11) for scenario [2, 1, 3] as shown in Box III.
- **Policy 4:** Model (11) for scenario [2, 3, 1] as shown in Box IV.
- **Policy 5:** Model (11) for scenario [3, 2, 1] as shown in Box V.
- **Policy 6:** Model (11) for scenario [3, 1, 2] as shown in Box VI.

The values for all strategies are graphically shown in Figure 6. Consequently, considering the order $[1,3,2]$, the locations should be checked to minimize the expected cost and expected time of the search.

Unfortunately, the above procedure is not practically useful. Obviously, this combination of SDP and MOP is not simple to carry out for medium or even

$$Z_{[1,2,3]} = \frac{C_1 + (1-\alpha_1 P_1)[C_2 + (1-\frac{\alpha_2 P_2}{1-\alpha_1 P_1}) \times C_3] - 0.0165}{0.0165} + \frac{t_1 + (1-\alpha_1 P_1)[t_2 + (1-\frac{\alpha_2 P_2}{1-\alpha_1 P_1}) \times t_3] - 0.021}{0.021}$$

$$= 4450.28 \Rightarrow Z_{[1,2,3]} = 4450.28.$$

Box I

$$Z_{[1,3,2]} = \frac{C_1 + (1-\alpha_1 P_1)[C_3 + (1-\frac{\alpha_3 P_3}{1-\alpha_1 P_1}) \times C_2] - 0.0165}{0.0165} + \frac{t_1 + (1-\alpha_1 P_1)[t_3 + (1-\frac{\alpha_3 P_3}{1-\alpha_1 P_1}) \times t_2] - 0.021}{0.021}$$

$$= 4372.05 \Rightarrow Z_{[1,3,2]} = 4372.05.$$

Box II

$$Z_{[2,1,3]} = \frac{C_2 + (1-\alpha_2 P_2)[C_1 + (1-\frac{\alpha_1 P_1}{1-\alpha_2 P_2}) \times C_3] - 0.0165}{0.0165} + \frac{t_2 + (1-\alpha_2 P_2)[t_1 + (1-\frac{\alpha_1 P_1}{1-\alpha_2 P_2}) \times t_3] - 0.021}{0.021}$$

$$= 4702.99 \Rightarrow Z_{[2,1,3]} = 4702.99.$$

Box III

$$Z_{[2,3,1]} = \frac{C_2 + (1-\alpha_2 P_2)[C_3 + (1-\frac{\alpha_3 P_3}{1-\alpha_2 P_2}) \times C_1] - 0.0165}{0.0165} + \frac{t_2 + (1-\alpha_2 P_2)[t_3 + (1-\frac{\alpha_3 P_3}{1-\alpha_2 P_2}) \times t_1] - 0.021}{0.021}$$

$$= 4903.68 \Rightarrow Z_{[2,3,1]} = 4903.68.$$

Box IV

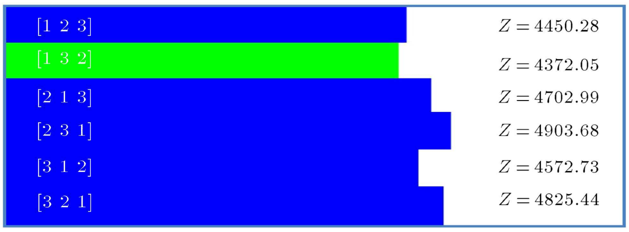

Figure 6. All possible search sequences.

small values of n. In other words, this problem is too hard to solve in the ordinary sense. It is noteworthy that for the optimization problem, diverse origins of difficulty, including the huge number of solutions and the intricacy of objective functions, can be considered. Clearly, we face all these factors in the suggested model. After the sensitivity analysis, we will try to diminish this difficulty.

5.4. Sensitivity analysis

To facilitate investigation into the performance of the suggested model, a sensitivity analysis is carried out. Sensitivity analysis is the study of how change of a parameter can influence the solution generated by the model when the others are constant. Now, we conduct the sensitivity analysis with variations in the cost and time of the model. In other words, when a specific parameter, e.g., time or cost, is changed and the others are constant, variation in the result of the model demonstrates its sensitivity to the specific parameter. According to Figure 7, the model is insensitive to increase in the value of cost after near 43% from the beginning of its range, namely 32.9. Please see Figure 7 for $C_1 = 25, 28, 30, 32, 32.9$.

Also, according to Figure 8, the model is insensitive to increase in the value of time after near 74% from the beginning of its range, namely 33.1. Please see Figure 8 for $t_1 = 20, 25, 30, 33, 33.1$.

Clearly, the sensitivity analysis has been conducted only for this very small case of the search problem and the greater cases for larger quantities of

$$Z_{[3,2,1]} = \frac{C_3 + (1-\alpha_3 P_3)[C_2 + (1-\frac{\alpha_2 P_2}{1-\alpha_3 P_3}) \times C_1] - 0.0165}{0.0165} + \frac{t_3 + (1-\alpha_3 P_3)[t_2 + (1-\frac{\alpha_2 P_2}{1-\alpha_3 P_3}) \times t_1] - 0.021}{0.021}$$

$$= 4825.44 \Rightarrow Z_{[3,2,1]} = 4825.44.$$

Box V

$$Z_{[3,1,2]} = \frac{C_3 + (1-\alpha_3 P_3)[C_3 + (1-\frac{\alpha_1 P_1}{1-\alpha_3 P_3}) \times C_2] - 0.0165}{0.0165} + \frac{t_3 + (1-\alpha_3 P_3)[t_1 + (1-\frac{\alpha_1 P_1}{1-\alpha_3 P_3}) \times t_2] - 0.021}{0.021}$$

$$= 4572.73 \Rightarrow Z_{[3,1,2]} = 4572.73.$$

Box VI

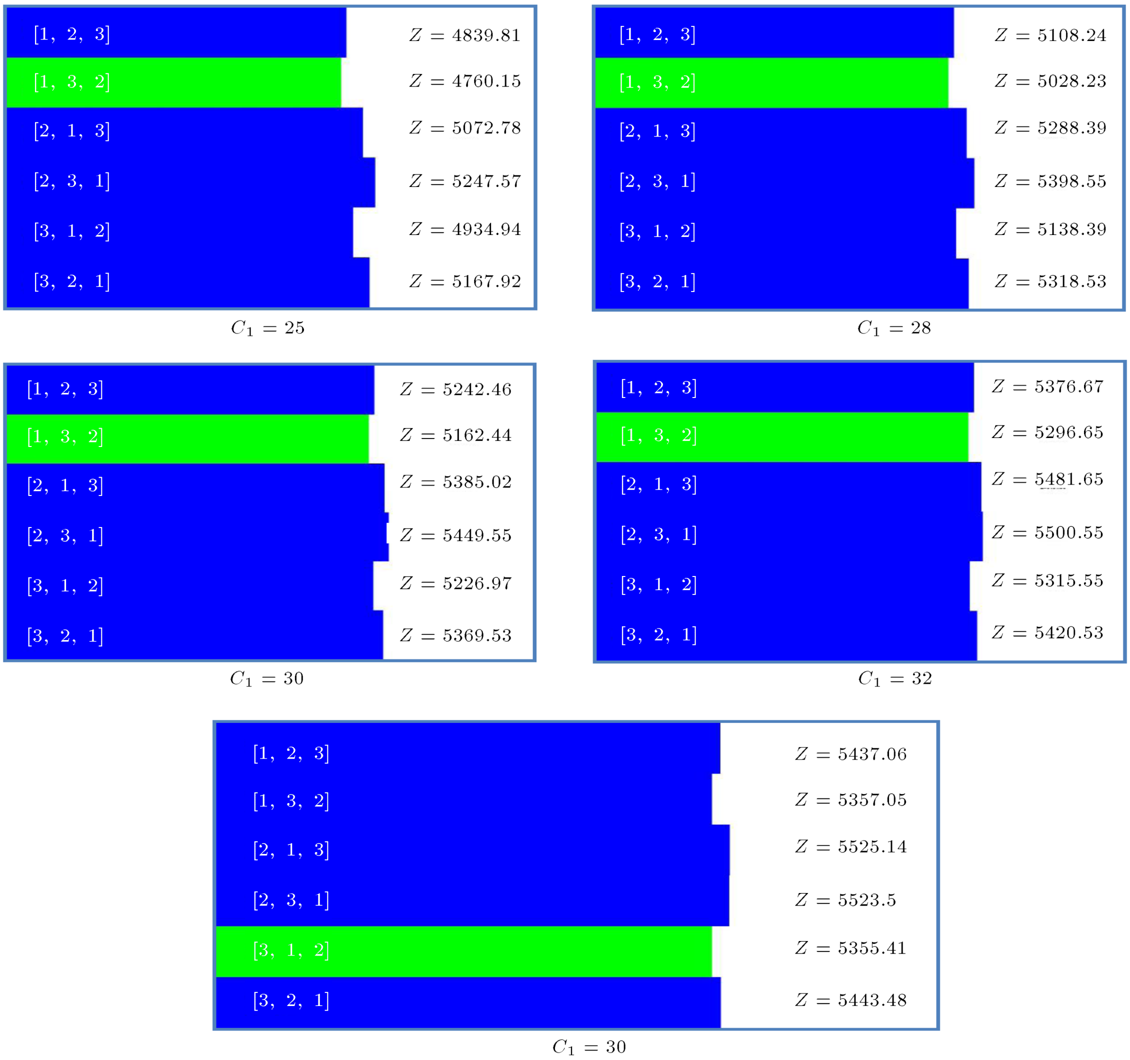

Figure 7. Sensitivity analysis for different values of search cost.

n require too much calculation time. As explained by many researchers, stochastic multi-objective structure for most of the problems is often hard to implement. Also, it is essential to mention that several MOPs on the basis of DP are close to unfeasible to optimize for practically sized problems. It is noteworthy that, as pointed out by [10], DP approach has been restricted to the problems with 2 or 3 state variables. Although for small cases, we try to employ exact method based on SDP, the computational efforts rise exponentially with the number of locations. On the other hand, in emergency situations, an operational problem should be solved within a limited time. However, exact algorithms such as SDP are time-consuming and very difficult to use in such problems. As stated before, optimization does not fundamentally emphasize only obtaining the global optimum solution to a problem. For example, Su et al. [71] mentioned that the optimum solution to the manifold emergency resources problem based on integer programming was very difficult and lengthy to obtain. Thus, they concentrated on another method to solve this problem for finding a suboptimal solution in a rational time. Consequently, in the next section, we will suggest an approximate approach on the basis of MCDM for the suggested search problem.

6. Alternative model based on MCDM framework for search problem

Although SDP prepares a potent tool for stochastic optimization, it is not easy to apply to large-scale search problems. Also, we observed in a computational case that stochastic multi-objective frame for search problem usually needed huge computational effort. In this part, as an alternative solution, an MCDM framework is adapted for the search problem. The model discussed in this part is the assessment of locations for the optimal search. To this end, a ranking of locations needs to be found. In other words, the goal of this problem is to order choices (locations) in the presence

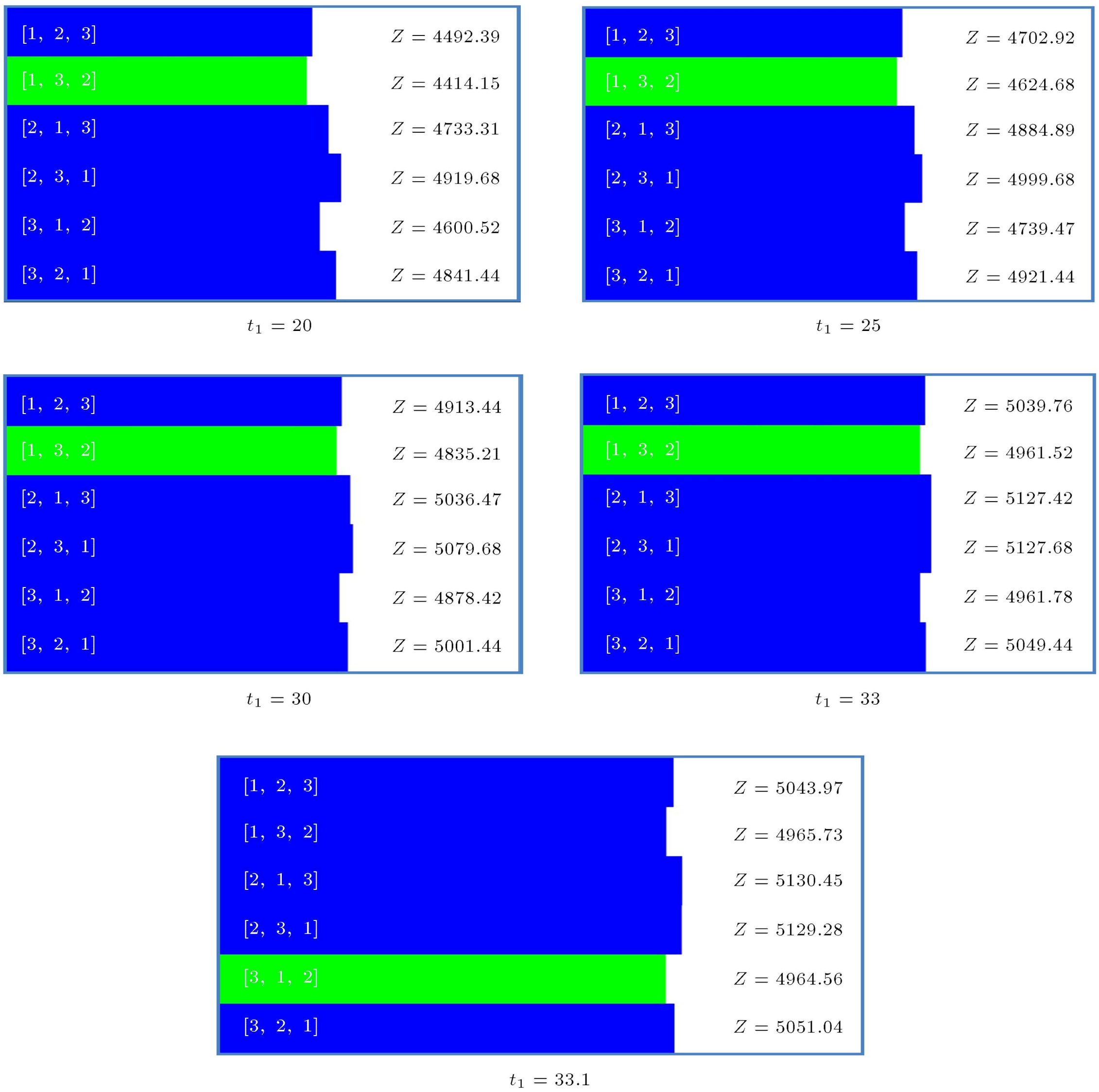

Figure 8. Sensitivity analysis for different values of search time.

in the presence of various attributes. Therefore, an MCDM approach that has the aptitude to give a complete ordering of options is essential. Generally, MCDM methods obtain the best choice among the possible options by considering diverse conflicting decision factors [72]. It should be noted that usually the complexities of MOP and SDP are obvious and the software for solving these methods is relatively scarce. Fortunately, nearly all MCDM methods are relatively straightforward and the software for solving them is available. Now, we reformulate the search problem as an MCDM framework; that is, we reduce the MOP into an MCDM problem. Consequently, the computational effort is decreased considerably and a good solution is produced.

6.1. Multi-Criteria Decision Making (MCDM)

Let us begin with explanation of the typical MCDM model. An MCDM framework can be depicted as follows:

$$D = \begin{array}{c} \\ A_1 \\ A_2 \\ . \\ . \\ . \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \dots & C_n \end{array} \\ \begin{bmatrix} x_{11} & x_{12} & \dots. & x_{1n} \\ x_{21} & x_{21} & \dots. & x_{2n} \\ . & . & & . \\ . & . & & . \\ . & . & & . \\ x_{m1} & x_{m2} & \dots. & x_{mn} \end{bmatrix} \end{array}$$

$$W = [w_1, w_2, ..., w_n], \tag{12}$$

where D is the decision matrix; $A_1, A_2, ..., A_m$ are feasible options among which the expert has to select one; $C_1, C_2, ..., C_n$ are the criteria with which choices are measured; x_{ij} is the rating of A_i with regards to C_j; and w_j is the weight of C_j.

First, D should be normalized so that it becomes dimensionless to allow for comparison. There are various normalization techniques [73]. Also, obtaining the suitable weights for all attributes is one of the key steps in the majority of MCDM methods. These techniques can be divided into two main categories [74]:

1. Subjective methods that obtain weights only by considering the preferences of experts, and
2. Objective methods that obtain weights by solving mathematical approaches without reflection on the preferences of the experts.

Obviously, opinion of the experts should be considered in the majority of the real problems. Therefore, subjective techniques can generally be more desirable. However, when providing a set of reliable subjective weights is not easy, the application of objective weights is beneficial. Among the objective techniques, Shannon entropy is one the most popular. In this work, the weight of each attribute is identified using Shannon entropy. Also, in MCDM approaches, the criteria will be categorized into two groups; the criteria that should be maximized are benefit factors and the criteria that should be minimized are cost factors.

As mentioned by Sun and Li [75], more than 70 MCDM methods have been presented. Although the goal of all these techniques is to help making a good decision, as pointed out by Zanakis et al. [76], various MCDM approaches may result in conflicting outcomes when applied to the same problem. Vincke [77] mentioned that choosing of an MCDM technique should be performed skillfully based on the nature of the problem, measurement scales, dependency of criteria, the amount of alternatives, form of ambiguity, and expectation of the experts. According to Lϕken [78], we often cannot conclude that one method is better than the others for a general problem. In other words, no one MCDM method is selected as the most appropriate for all problems. But, a number of MCDM methods better suit a given problem than others do. Therefore, MCDM techniques have been compared in several studies. However, the majority of researchers avoid selecting a single MCDM technique over another, because such assertion would require a firm theoretical base or evaluation for numerous real cases [79].

As mentioned, up to now, several MCDM techniques have been introduced. However, selection of a proper MCDM technique is an intricate MCDM problem [75]. Transparency is one of the most essential factors that should be addressed in choosing an MCDM technique [80]. If an expert does not realize what is taking place within the MCDM procedure, the outcome may be that the expert does not trust the suggestion of the approach [78]. Simplicity and computation time are two important criteria in selecting an MCDM technique. As pointed out by Chatterjee et al. [80], it is recommended not to employ a very intricate MCDM approach without transparency, because it becomes very difficult for a user to recognize any mistake made throughout the computation procedure.

Chatterjee et al. [80] compared COPRAS, TOPSIS, VIKOR, and AHP in a material selection problem on the basis of simplicity, transparency, calculation time, etc. According to that study, COPRAS is straightforward to employ and very good in transparency. Also, it has a low calculation time. On the other hand, although AHP is one of the most broadly used MCDM techniques, it is a very controversial method. For example, AHP method suffers from numerous pairwise evaluations [78]. Also, if the pairwise assessment is recognized to be inconsistent, the expert should execute this task again. In other words, AHP mathematically has an intricate procedure [80].

Antucheviciene et al. [81] evaluated the results of VIKOR, TOPSIS, and COPRAS in building redevelopment problem and deduced that COPRAS and TOPSIS were superior to VIKOR. It is noteworthy that VIKOR is one of the popular MCDM methods. However, Huang et al. [82] warned that VIKOR might generate an incorrect ranking in some cases. Also, according to [83], TOPSIS method may have higher distinguishing ability due to vector normalization. Peng [84] appraised TOPSIS, VIKOR, ELECTRE, PROMETHEE, GRA, and WSM in the earthquake vulnerability problem. In their study, TOPSIS was chosen as the most trustable technique. Sun and Li [75] assessed 24 MCDM techniques such as TOPSIS, ELECTRE, AHP, SAW, etc. in the aircraft selection problem. In this study, TOPSIS was chosen as the most proper technique. On the basis of an extensive literature review, Mousavi-Nasab and Sotoudeh-Anvari [85] revealed that TOPSIS and COPRAS were the best MCDM methods for the general material selection problem. However, in some problems, there is not a solid reason to select a specific MCDM method. For example, Athawale and Chakraborty [86] compared 10 MCDM techniques such as VIKOR, AHP, TOPSIS, GRA, ELECTRE, PROMETHEE, WPM, etc. in robot selection problem. According to this comparison, all the aforementioned techniques provide very similar orderings of the alternatives. Mulliner et al. [83] analyzed some MCDM methods such as revised AHP, TOPSIS, COPRAS, WSM, etc. in a sustainable housing affordability problem; they deduced that none of these techniques were perfect. Accordingly, Mulliner et al. [83] suggested that more than one technique should be employed for a problem to make a firmer decision. However, when use of several MCDM techniques is not feasible, COPRAS should be employed. Mela et al. [79] presented a comparison among VIKOR, WPM, TOPSIS, SAW, and PROMETHEE for a building design problem. They inferred that the best MCDM techniques would hardly be acquired. The reader can see [72] and [87] for two comparative studies of MCDM methods.

It is a well-known approach to employ more than one MCDM method to handle a given prioritizing problem [88]. Thus, we select two MCDM approaches, namely COPRAS and TOPSIS, to prioritize the search locations for several reasons. First of all, the ordering concurred by two MCDM techniques is more reliable than a result produced by one MCDM technique. Furthermore, COPRAS and TOPSIS allow for benefit as well as cost factors to be combined in one analysis without complexity. But, for example, cost factors in AHP and WSM should be converted into benefit factors before normalization [83]. In addition, COPRAS and TOPSIS can provide a perfect ranking of options. But, for example, ELECTRE and PROMETHEE cannot often give a full ordering of the choices. Also, these two methods require large expert interaction in solving procedures. Hence, ELECTRE and PROMETHEE are unsuitable for our problem. In contrast, TOPSIS and COPRAS perform well with numerous choices and criteria [72,83]. Let us point out that the only aim of this subsection is not to declare which MCDM technique is the best. Rather, our key aim is to highlight that the use of two (or more) MCDM techniques can generate more reliable results.

In brief, some main reasons that we choose TOPSIS and COPRAS for this problem are as follows:

1. The idea behind TOPSIS and COPRAS is logical as well as easy to realize and use. As Lϕken [78] mentioned, for many decision makers, ELECTRE is complicated to understand and utilize. Velasquez and Hester [89] pointed out that one of the important shortcomings of ELECTRE was that its procedure and results could be difficult to elucidate for a layman. Also, AHP and PROMETHEE are computationally intricate and need intervention of the user. In these methods, subjective judgments have large influence on the results;
2. Calculation procedures of TOPSIS and COPRAS can be simply programmed;
3. TOPSIS and COPRAS can be employed efficiently when the amount of alternatives or selection factors is large. In contrast, AHP, PROMETHEE, and ELECTRE are time-consuming in this situation and their performance is attenuated rapidly when the quantity of options or attributes is large [72,85];
4. TOPSIS and COPRAS are easily applied with positive and negative decision factors with one procedure. In contrast, in AHP and SAW, negative criteria must be transformed into positive criteria before normalization. Millet and Schoner [90] revealed that this transformation might lead to computational difficulty and extract incompatible outcomes in AHP;
5. TOPSIS and COPRAS offer a full ranking of options. In contrast, ELECTRE and PROMETHEE are sometimes unable to determine the best choice. For example, Özcan et al. [72] pointed out that since ELECTRE did not give a complete ranking in some situations, it might suggest plural solution as the best choice. A plural solution is two or more options that find the same ranking;
6. The TOPSIS and COPRAS results are not influenced by any additional parameter. In contrast, for example, VIKOR result relies on parameter severely [79]. Also, in PROMETHEE, unsuitable tuning of parameters can generate incoherent outcomes;

It is important to mention that, as literature review shows, SAW and AHP can be considered as the most frequently used MCDM techniques [89]. However, some points about these two MCDM methods should be made. Since the introduction of AHP, there has been widespread argument about the theoretical truth of this technique. These arguments have focused on four points: the axiomatic foundation, the true meaning of the weights of criteria, the measurement scale, and the rank reversal phenomenon [91]. Also, although SAW is the simplest and probably the most generally used MCDM technique, as Velasquez and Hester [89] warned, in some cases, the outcome provided by SAW may not be reasonable. Besides, Mulliner et al. [83] pointed out that WPM was a straightforward method, but its disadvantage was that benefit-type and cost-type criteria should not be utilized simultaneously.

6.2. Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)

TOPSIS, as one of the most famous MCDM techniques, was first suggested by Hwang and Yoon [92]. The preferred choice is the closest to the ideal solution and farthest from the anti-ideal solution. TOPSIS is a compensatory approach and allows for tradeoffs among decision attributes. It is noteworthy that TOPSIS has been effectively employed in tremendous real applications [84,85,93,94].

The steps of TOPSIS are explained as follows:

Step 1: Normalize the decision matrix (D) using the following formula:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{j=1}^{n} x_{ij}}} \quad i = 1, 2, ..., m; \; j = 1, 2, ..., n. \tag{13}$$

Step 2: Provide weight for this matrix by:

$$v_{ij} = w_j \times r_{ij} \quad i = 1, 2, ..., m; \; j = 1, 2, ..., n, \tag{14}$$

where w_j is the weight of attribute j and $\sum_{j=1}^{n} w_j = 1$.

Step 3: Specify the ideal solution and anti-ideal solution using Model (13):

$$A^* = \{v_1^*, v_2^*, ..., v_n^*\}$$

$$= \{(\max_j v_{ij} \,|i \in I'), (\min_j v_{ij} \,|i \in I'')\},$$

$$i = 1, 2, ..., m; \; j = 1, 2, ..., n.$$

$$A^- = \{v_1^-, v_2^-, ..., v_n^-\}$$

$$= \{(\min_j v_{ij} \,|i \in I'), (\max_j v_{ij} \,|i \in I'')\},$$

$$i = 1, 2, ..., m; \; j = 1, 2, ..., n, \qquad (15)$$

where I' is related to benefit factors and I'' is related to cost factors.

Step 4: Obtain the distance of each option from A^+ and A^- using the following equations (the n-dimensional Euclidean distance):

$$D_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^+)^2} \qquad i = 1, 2, ..., m,$$

$$D_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2} \qquad i = 1, 2, ..., m. \qquad (16)$$

Step 5: Obtain the comparative closeness to the ideal solution by:

$$CC_i^* = \frac{D_i^-}{D_i^- + D_i^+} \qquad i = 1, 2, ..., m. \qquad (17)$$

Step 6: Rank the choices according to CC_i^*. The bigger CC_i^*, the better choice A_i.

6.3. *Complex Proportional Assessment (COPRAS)*

COPRAS method, which was introduced by Zavadskas et al. [95], considers straight (direct) and relative (proportional) dependences of the priority (significance) and utility degree of the options with regards to the mutually incompatible attributes. This technique chooses the best option considering the ideal solution and the ideal-worst solution [80]. Similar to TOPSIS, COPRAS is a compensatory technique. Also, owing to its distinguishing features, COPRAS has been effectively employed in various fields [80,81,83,85].

The procedure of COPRAS is explained below [80]:

Step 1: Similar to most MCDM methods, normalize D by:

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}. \qquad (18)$$

Step 2: Provide weight for this matrix by:

$$y_{ij} = w_j \times r_{ij} \qquad i = 1, 2, ..., m; \; j = 1, 2, ..., n.$$

In the above-mentioned equation, r_{ij} is the normalized value of choice i of attribute j and w_j is the weight of factor j. Using this alteration, the total dimensionless weighted value of every attribute equals the weight of that attribute:

$$\sum_{i=1}^{m} y_{ij} = w_j. \qquad (19)$$

Step 3: Obtain the sum of Weighted Normalized Values (WNV) by:

$$S_{+i} = \sum_{j=1}^{n} y_{+ij},$$

$$S_{-i} = \sum_{j=1}^{n} y_{-ij}, \qquad (20)$$

where y_{+ij} and y_{-ij} are the WNVs for the positive (beneficial) and negative (non-beneficial) criteria, respectively. The greater S_{+i}, the superior is the option and the lower is S_{-i}; therefore, the better is the choice. Note that S_{+i} and S_{-i} indicate the levels of goals reached by every choice.

Step 4: Obtain the priorities of the choices by defining the positive option S_{+i} and negative option S_{-i} traits. The comparative significance Q_i of each A_i is calculated by:

$$Q_i = S_{+i} + \frac{S_{-\min} \sum_{i=1}^{m} S_{-i}}{S_{-i} \sum_{i=1}^{m} \frac{S_{-\min}}{S_{-i}}} \qquad i = 1, 2, ..., m. \quad (21)$$

In the above-mentioned equation, $S_{-\min}$ indicates the minimum S_{-i}. The greater Q_j, the higher the significance of the option. Thus, the choice with the highest relative priority ($Q_{\max}$) is the best option.

Step 5: Determine the level of utility (U_i) for choice i. U_i (absolute prioritizing) is calculated by:

$$U_i = \frac{Q_i}{Q_{\max}} \times 100. \qquad (22)$$

To specify the adaptability of these two MCDM techniques, namely TOPSIS and COPRAS, their comparative accomplishments are compared by the Spearman's rank correlation test.

6.4. Spearman's Rank Correlation Coefficient (SRCC)

SRCC is employed to obtain the measure of relationship (agreement) between results (ranks) generated by various MCDM techniques. If R_i and $R_{i'}$ indicate the results obtained by two various MCDM techniques for alternative i and m is the number of options, then SRCC will be calculated as follows:

$$r_s = 1 - 6\frac{\sum_{i=1}^{m}(R_i - R_{i'})^2}{m(m^2-1)}. \quad (23)$$

The bigger r_s, the better the association is between the two techniques. Please note that $r_s = 1$ shows complete agreement, $r_s = -1$ shows complete disagreement, and $r_s = 0$ indicates no relationship between the results. The reader can refer to [81] and references therein to study further about SRCC.

6.5. MCDM-based method for search problem

In this part, we introduce a multiple-criteria evaluation framework for the search problem.

6.5.1. Problem description and solution

Suppose that a motionless target is located or hidden in location i and this goal does not react to the activity of the searcher. Please note that the number of locations is known. The probability that the goal is in location i is P_i and it is clear that $\sum_{i=1}^{n} P_i = 1$. The search cost and search time of location i are C_i and t_i, respectively. Again, in this problem, a wounded man trapped under debris is the "target" and the positions where a missing person has probably been before a disaster are "locations". Now, the aim of this problem is prioritization for the search of locations. In other words, the model prioritizes the given locations based on three weighted attributes, namely search cost, search time, and probability of finding the goal. It should be noted that various criteria are significant in studying the search problem as an MCDM problem. From [14,17,26,32,43], the criteria for the prioritization of locations can be identified. More formally, we select four of them, which correspond to the previous two objectives as follows:

1. Search cost;
2. Search time;
3. Probability that the goal is in location;
4. Overlook probability.

Let us reconsider the case that was presented in Sub-section 5.2. We consider three attributes, i.e., search cost, search time, and probability of detecting the goal. In this case, without loss of generality, we suppose the probability of overlook is zero, i.e., $\forall i, \alpha_i = 1$. Among these three attributes, probability of finding the goal is the beneficial criterion. On the other hand, search cost and search time are non-beneficial criteria. Three locations are considered as the candidates. From these three choices, the one with the highest priority should be chosen. Table 5 demonstrates the ratings of the locations regarding the selected attributes on the basis of Tables 2, 3, and 4. Now, the weights of attributes should be calculated. In this work, the weights of criteria are obtained by using Shannon entropy. Shannon entropy values of the attributes are calculated as follows. We have:

$$E_j = -\frac{1}{\ln m}\sum_{j=1}^{n} p_{ij}\ln p_{ij},$$

where:

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}},$$

and the weights will be calculated by:

$$w_j = \frac{1-E_j}{\sum_{j=1}^{n} 1-E_j}.$$

Thus, to prioritize the locations by TOPSIS and COPRAS, weights of attributes are specified using Shannon entropy as shown in Table 6.

Finally, we run COPRAS and TOPSIS, and obtain the rankings of alternatives, separately. According to Table 7, COPRAS gives the rankings of locations as 1-3-2. Also, TOPSIS gives the rankings of locations as 1-3-2. Hence, based on the order [1, 3, 2], the locations should be checked.

Figure 9 graphically demonstrates the rankings of locations. Clearly, the value of SRCC between TOPSIS and COPRAS is 1. Therefore, an important observation in the use of various MCDM techniques is that the outcome of TOPSIS is in excellent agreement

Table 5. Decision matrix.

	Search cost (thousand USD)	Search time (hour)	Probability of finding the goal
Location 1	23	19 h	38%
Location 2	25.5	17.5 h	28%
Location 3	30	16 h	34%

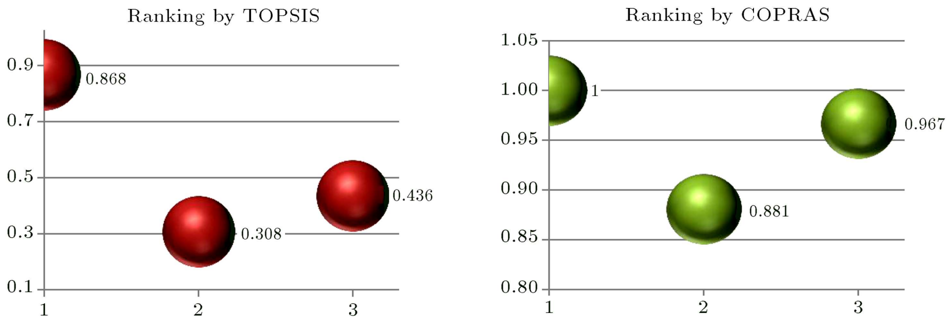

Figure 9. Rankings of locations (the horizontal axis shows the alternatives).

Table 6. Weights of criteria.

Criterion	Search cost	Search time	Probability that the goal is in location i
Weight	0.373	0.152	0.473

Table 7. Rankings of locations by two MCDM methods.

TOPSIS			COPRAS		
Location	Rank	Similarity ratio	Location	Rank	Degree of utility
Location 1 (cottage)	1	0.868	Location 1 (cottage)	1	1
Location 2 (forest)	3	0.308	Location 2 (forest)	3	0.881
Location 3 (mountain)	2	0.436	Location 3 (mountain)	2	0.967

with the result of COPRAS for this problem. It is noteworthy that this is consistent with the study of Mousavi-Nasab and Sotoudeh-Anvari [85].

Finally, it is important to note that although the models attained the same results, the calculation effort and computation time were intuitively smaller in MCDM-based model than in the stochastic multi-objective model for the suggested search problem.

7. Conclusion

Although SAR is one of the most vital operations for the earthquake DM, its various models have not been as accentuated as the models for transportation or location in this field. In this paper, we suggested a stochastic multi-objective model to optimize the search operation in the response stage of DM based on COSM. Due to sequential nature of the optimal search problem and stochastic organization of this model, we employed SDP technique to tackle this problem similar to COSM. The proposed framework minimized expected cost and expected time of search procedure successfully. However, the outcome obtained by the suggested model illustrated that computing time in real cases would be large. In other words, the stochastic multi-objective nature of the problem made it very intricate to find the optimal solution, even for small-size cases, using SDP. Therefore, we reformulated the search problem as an MCDM problem. This study showed that not only MCDM methods were workable for the search problem, but also the use of MCDM methods seemed inevitable for coping with large cases. Due to their outstanding features, TOPSIS and COPRAS were employed to rank the locations. The observation indicated an excellent agreement between TOPSIS and COPRAS in the search problem.

Let us now note a number of directions for future research. The development of the proposed stochastic multi-objective framework for the search problem in the presence of various constraints is remarkable. Also, heuristic methods can be proposed to handle large problems. Furthermore, it can be very interesting to introduce an MCDM framework when MCDM techniques produce conflicting results.

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