Mitigating the consequences of disruptions by locating temporary facilities and balancing the redistribution of users

Predrag Grozdanović[1,*] **and Miloš Nikolić**[1]

[1] *University of Belgrade, Faculty of Transport and Traffic Engineering, Vojvode Stepe 305, Belgrade, Serbia*
E-mail: ⟨*{p.grozdanovic, m.nikolic}@sf.bg.ac.rs*⟩

Abstract. Many service systems are subject to disruptions that can reduce their operational capacity, forcing users to find alternative ways to meet their service needs. One way to mitigate such effects is to locate temporary facilities where users can receive services. Also, users can be served in facilities unaffected by the disruptions. This paper considers the problem of locating temporary facilities after a disruption and redistributing users to minimize the average travel distance. Compared with existing models, the proposed approach allows limited overcapacity and balances it across facilities to ensure a more even redistribution of users. A mathematical formulation of mixed integer programming is proposed and used to determine the locations of temporary facilities and the balanced redistribution plan. The final number of temporary facilities is determined using a TOPSIS method. The proposed approach integrates an exact approach with the TOPSIS method and enables the straightforward addition of new criteria without modifying the mathematical formulation. Testing on small-sized hypothetical examples demonstrates that, without capacity constraints, overcapacity in some facilities can reach 150%, whereas the proposed approach limits it to 45% and balances it so that differences among facilities do not exceed 10%. The results of testing illustrate that the proposed approach effectively solves the multi-objective location and redistribution problem while avoiding computationally intensive methods such as multi-criteria optimization or metaheuristics. The proposed approach provides a flexible and implementable framework that balances system management and user objectives under disruptions.

Keywords: allocation of users, capacity constraints, disruption events, facility location, temporary facilities

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1. Introduction

Many service systems are susceptible to disruptions that can reduce their ability to operate. As a result, many users have to find alternative ways to meet their service needs. One way to mitigate the negative effects of the disruption is to locate new temporary facilities where users can receive the desired services. Unfortunately, such events have become increasingly frequent in recent years. A disruption in the system can be acted on before or after disruptions (pre-disruption or post-disruption). Most of the papers in the literature propose approaches that ensure greater resistance of systems and their users to disruptions (pre-disruption) [7] and [1]. Fewer papers in the literature deal with the post-disruption period [3]. The response to a disruption after its occurrence ensures the immediate protection of people's health and

*Corresponding author.

lives by establishing temporary facilities and plans to return the system to the state before the disruption as soon as possible [8].

In case of various natural disasters, terrorist attacks, or other causes of disruption, one or more facilities in the system may be closed. One possible response is to develop a plan for redistributing users affected by the disruption to active facilities. However, such a way of responding to a disruption can only be applied in the case of disruptions of smaller dimensions. To overcome disruptions of larger dimensions, the introduction of temporary facilities must be considered. Creating a plan to redistribute users affected by the disruption to active permanent facilities (PF) and locate temporary facilities (TF) allows users to receive services in an acceptable time frame.

The importance of introducing temporary facilities after a disruption, when it is important to allocate resources quickly and efficiently, was highlighted in a review paper [2]. The authors provide a detailed review of the literature, including 65 papers that address location theory problems associated with the introduction of temporary facilities. One of the most famous location problem is the p-median problem [11]. The p-median model with capacity constraints is known as the capacitated p-median model. The p-median problem is much more often solved in the literature compared to the capacitated p-median problem. In the capacitated p-median problems [12] and [10], as well as in many p-median problems, redistribution of users from one node to one facility is allowed. This paper proposes a model based on the capacitated p-median problem, which enables the redistribution of users from one node to one or more facilities.

Unsatisfied demand is a problem that often occurs after disruptions in the system, especially in the case of capacity constraints. In the literature, there are papers dealing with the minimization of unsatisfied demand [4] and [6]. In the case of unsatisfied demand, fictitious facilities must be introduced, which is the case with classic capacity constraints [10]. Various forms of capacity constraints are used in the literature [12] and [4]. Common to those constraints is that they lead to the situation that if there is not enough capacity, not all users will receive the service. Capacity constraints designed in this paper allow all users to receive the requested service. This is achieved by introducing temporary facilities and allowing overcapacity to a certain limit, which enables normal functioning of the facility. These constraints solve the problem of unsatisfied demand while maintaining the efficiency of the system.

The use of hybrid approaches, which integrate the Exact Approach (EA) with multi-attribute decision-making (MADM) methods, is common in location problems under disruption conditions. MADM methods are most often used in the first phase, which includes the analysis of locations, to generate a set of potential locations of temporary facilities [5] and [14]. Unlike the papers in the literature, in this paper, the TOPSIS method was used after applying the optimization model (second phase) in order to select the best solution. By combining the EA for solving the capacitated p-median problem with the TOPSIS method (the EA-TOPSIS approach), several issues observed in the literature are addressed, such as the redistribution of users from one node to multiple facilities, unsatisfied demand, facility overloading, and non-balanced user redistribution plans. In related studies, similar problems are frequently addressed using robust, stochastic, or bi-level models, which require complex optimization methods for their solutions. Due to the conflicting objectives of minimizing user travel distance and limiting the number of temporary facilities, the considered problem has a multi-objective structure. Without the proposed hybrid framework, it would typically require multi-objective optimization or metaheuristic solution methods [9] and [1]. The developed EA-TOPSIS approach overcomes this by separating optimization and decision evaluation, thereby reducing methodological and computational complexity.

In this paper, a location model was developed that determines the location of TFs and creates a new plan for the redistribution of users allocated to the closed PFs. A temporary facility can be located at any demand node where there is no permanent facility. System adaptation to disruption is also reflected in the possibility of exceeding the capacity of PF and

TF to a certain limit. To evenly redistribute users across the functioning facilities, overcapacity balancing constraints have been implemented. The goal of the developed model is to minimize the average distance traveled by users affected by the disruption to obtain the requested service. It is in the interest of the system to overcome the consequences of the disruption with as few TFs located as possible. However, a smaller number of TFs affects the increase in the distance traveled by users and greater overcapacity in facilities. To create a balance between the system's goal and its users, the TOPSIS method is combined with a developed mathematical formulation to determine the number and location of TFs. In this way, the solution obtained by combining the EA and the TOPSIS method (EA-TOPSIS) represents a compromise between increasing the distance traveled by users and reducing the number of TF locations. We tested the EA-TOPSIS approach on a hypothetical example of 20 demand nodes and 5 PFs and obtained high-quality results. The obtained results confirm the possibility of direct application of the developed EA-TOPSIS approach in practice. The EA-TOPSIS approach can be applied to various systems, such as justice systems, police systems, healthcare systems, and other systems in which a single facility serves users from a particular region.

Several main contributions are highlighted in this paper. First, a mixed-integer location model is developed to simultaneously determine the locations of TFs and the redistribution plan for users affected by disruptions. Second, the model allows the redistribution of users from a single demand node to multiple facilities, enabling more flexible system adaptation under disruption conditions. Third, overcapacity balancing constraints are implemented, enabling controlled overcapacity in both PFs and TFs and ensuring an even redistribution of users across functioning facilities. Finally, an EA–TOPSIS hybrid approach is developed for determining the number and locations of TFs, and its practical applicability is demonstrated through computational testing.

This paper is organized as follows. Section one presents the introductory remarks and highlights the main contributions of the paper. The second section provides a description of the considered problem, its mathematical formulation, and the TOPSIS method that is adapted for application and combination with the previously given mathematical formulation. The developed EA-TOPSIS approach is then tested on a hypothetical example, and the test results are presented in the fourth section. Concluding remarks are given at the end of the paper.

2. Methodology

In this section, the problem and the system's response to disruptions are presented, along with the proposed EA–TOPSIS approach. The following subsections detail the mathematical formulation of the capacitated p-median model and the TOPSIS method.

2.1. Problem description and proposed approach

The problem considered in this paper is inspired by the functioning of systems in which a single facility provides services to all users in the region in which it is located. A region encompasses one or more municipalities in which users live. In such systems, all users of a region gravitate to a single facility and can only receive the requested service in that facility. Under normal conditions, users can only request service in the preassigned facility. They cannot receive service in any of the facilities from other regions. The most common examples of such systems are public buildings owned by the state, such as municipal buildings, courts, police, health institutions, etc.

A challenge in the operation of the described systems may arise if a facility in one region is affected by a disruption. In the event of an attack on one or more facilities, users preassigned to that facility or those facilities must be redistributed to active facilities (non-closed). In this case, due to the reduction in the number of operational facilities (non-closed facilities), overcapacity of the facilities is permitted. The permitted overcapacity of facilities and the location of TFs will ensure that the consequences of disruption (attacks on one or more facilities) are as minimal as possible.

All municipalities in which there is no PF were taken as potential locations for TFs. The placement of TFs is considered with the following constraints. Only one TF can be established at each potential location. A TF cannot be established at the locations of the PF and, therefore, not at the site of the disruption. When addressing the described problem, it is necessary to determine which facilities are under attack and the maximum number of TFs that can be located. By resolving the stated issue, a solution is produced that identifies the number and location of TFs, as well as the redistribution of users affected by the disruption. The aim of solving this problem is to minimize the impact of the disruption on both users and the system. More specifically, the aim is to minimize the average distance traveled by users affected by the disruption to access the required service, while optimizing the number of located TFs, and balancing overcapacity in facilities.

Locating a larger number of TFs will reduce the consequences of disruptions, but will result in high construction costs. However, locating too few TFs may cause users to feel the effects of disruptions. The goal in selecting the final solution is to find a balance between the number of TFs located and the average distance that users affected by the disruption travel to receive service. Therefore, the paper proposes an EA-TOPSIS approach that combines the EA, used to solve the proposed mathematical formulation, with the TOPSIS method for multi-criteria evaluation of the generated solutions. The methodological framework of the proposed EA-TOPSIS approach is illustrated in Figure 1. The approach consists of two sequential phases. In Phase I (EA), the capacitated p-median model is solved iteratively for an increasing number of temporary facilities until a predefined maximum p_{max} is reached, generating a set of feasible alternatives. In Phase II (TOPSIS), the generated alternatives are evaluated and ranked using the TOPSIS method, with criteria weights determined using the direct rating (DR) method. This process leads to the selection of the most suitable recovery configuration.

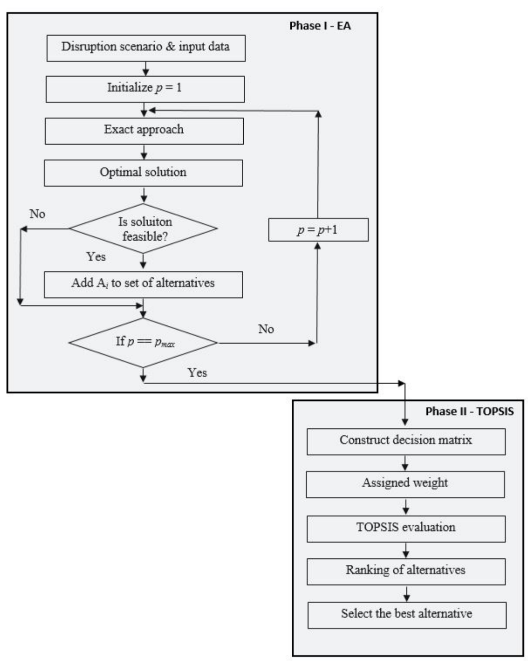


Figure 1: *Methodological framework of the proposed EA-TOPSIS approach.*

2.2. Mathematical formulation

This section presents the mathematical formulation of the considered problem. The notation used in the model is summarized in Table 1, listing all sets, parameters, and decision variables.

Sets	
P	set of locations of permanent facilities
T	set of potential locations of temporary facilities
F	set of all locations of facilities ($F = P \cup T$)
U	set of users represented by demand nodes (municipalities)
U_j	set of demand nodes preassigned to permanent facility j ($U_j \subseteq U, j \in P$) by territorial division
Parameters	
v_i	demand (number of users) at node i ($i \in U$)
p_{max}	the maximum number of temporary facilities that can be located
s_j	equals 1 if there is a permanent facility at location j, otherwise 0
r_j	equals 1 if a permanent facility at location j is closed, otherwise 0
d_{ij}	shortest distance between demand node i and facility j
Q_j	capacity of facility j
ρ	the maximum overcapacity ratio of the facility
β	the maximum tolerance of the difference in the overcapacity ratio between facilities
NAU	number of affected users in case of disruption
Decision variables	
x_j	$\begin{cases} 1, & \text{if the temporary facility is located at } j \ (j \in T) \\ 0, & \text{otherwise} \end{cases}$
y_j	$\begin{cases} 1, & \text{if the capacity of facility } j \text{ is exceeded} \\ 0, & \text{otherwise} \end{cases}$
z_j	overcapacity ratio of facility j ($j \in F$)

Table 1: *Notation used in the mathematical formulation.*

The mathematical formulation can be given in the following way:

$$\min Z = \frac{1}{NAU} \sum_{j \in F} \sum_{i \in U_j} d_{ij} q_{ij} \tag{1}$$

subject to:

$$\sum_{j \in T} x_j \leq p_{\max} \tag{2}$$

$$\sum_{j \in F} q_{ij} = v_i, \quad \forall i \in U \tag{3}$$

$$\sum_{\substack{l \in F \\ l \neq j}} q_{il} \leq v_i r_j, \quad \forall j \in P, \forall i \in U_j \tag{4}$$

$$q_{ij} \leq v_i (1 - r_j), \quad \forall i \in U, \forall j \in P \tag{5}$$

$$q_{ij} \leq v_i (s_j + x_j), \quad \forall i \in U, \forall j \in F \tag{6}$$

$$z_j \leq \rho y_j, \quad \forall j \in F \tag{7}$$

$$\sum_{i \in U} q_{ij} \geq Q_j(y_j + z_j), \quad \forall j \in F \tag{8}$$

$$\sum_{i \in U} q_{ij} \leq Q_j(1 + z_j), \quad \forall j \in F \tag{9}$$

$$z_j - z_l \leq \beta + \rho(2 - y_j - y_l), \quad \forall j, l \in F, \, j \neq l \tag{10}$$

$$x_j \in \{0, 1\}, \quad \forall j \in T \tag{11}$$

$$y_j \in \{0, 1\}, \quad \forall j \in F \tag{12}$$

$$q_{ij} \geq 0 \text{ and integer}, \quad \forall i \in U, \forall j \in F \tag{13}$$

$$z_j \geq 0, \quad \forall j \in F \tag{14}$$

The objective function (1) represents the average distance traveled by users affected by the disruption, and it should be minimized. This is achieved by redistributing the territorial assigned users from the closed facilities to the nearest non-closed facilities. Constraint (2) defines the maximum number of TFs that can be located. Constraints (3) to (6) apply to user flows. Constraints (3) ensure that all users receive the requested service. Constraints (4), (5), and (6) prevent the redistribution of users to a facility that is attacked, to a facility that does not exist, and to a temporary facility that is not located. Constraints (7) - (9) define the maximum allowed overcapacity ratio of the facility j. Constraints (10) also refer to the capacity of facilities, and they should achieve a balance between the overcapacity in the facilities, that is, they define the maximum allowed difference in the overcapacity ratio between facilities j and l. The decision variables in the model are defined over the following domains: binary variables x_j and y_j as specified in constraints (11) and (12), a non-negative integer variables q_{ij} as in constraints (13), and a non-negative continuous variables z_j as in constraint (14).

The proposed model is designed for universal applicability across different systems and incorporates fundamental criteria that are common to all of them. When applied to a specific system, additional criteria may be introduced, particularly cost-related components such as fixed costs for locating temporary facilities and travel costs generated by user movements. These elements can be incorporated through an appropriate modification of the objective function.

The model also includes user splitting and explicit overcapacity control. User splitting ensures that no demand remains unsatisfied, while overcapacity control prevents excessive load concentration at individual facilities. By balancing the overcapacity ratio among facilities, the model protects infrastructure resources and enhances operational sustainability. Such load balancing contributes to system stability, especially under disruption conditions, enabling a more resilient and flexible network response.

From a computational perspective, the resulting formulation is a mixed-integer linear programming (MILP) model. Due to the presence of binary and integer decision variables, the problem belongs to the class of NP-hard optimization problems.

2.3. Method for determining the number of temporary facilities

When solving the MILP model based on the proposed mathematical formulation, the number of TFs to be located must be determined in advance. The number of TFs can be determined in advance, based on available resources, or by applying the TOPSIS method after testing several scenarios regarding the number of located TFs. It should be noted that when applying only the EA, the maximum number of TFs to be located must be defined in advance. However, if the TOPSIS method is used, it is necessary to generate several solutions with different numbers of located TFs, based on which the best solution will be selected using the TOPSIS method. The

EA-TOPSIS approach selects the best solution from a set of generated feasible solutions based on defined criteria.

In certain situations, the proposed approach may be easier to implement than a full multi-objective optimization framework. This is particularly evident when the analyst intends to incorporate additional evaluation criteria that are difficult to formalize within a strict mathematical structure. Such criteria may include location suitability, accessibility, or other context-specific and partially subjective factors. In these cases, separating the generation of feasible solutions from their final evaluation allows greater modeling flexibility. Additional criteria can be introduced at the evaluation stage without reformulating the entire optimization model, which simplifies practical application and enhances adaptability to real-world decision-making environments.

The TOPSIS method is an MADM method used to select the best alternative from a set of alternatives [13]. In this paper, the TOPSIS method is applied to select the best solution from a set of solutions that represent a plan for locating TFs and redistributing users to PFs and TFs, after disruptions. The set of alternatives depends on the available number of TF that can be located, but also on whether the solution obtained by the EA approach is unique. In the case where all solutions are unique, the number of alternatives is equal to the maximum number of TF that can be located, increased by one ($p_{max} + 1$) (the alternative when the number of TF is zero). The number of alternatives can be even larger when the solution obtained by applying the EA approach is not unique. In this situation, more optimal solutions for the defined number of TF locations could be identified and inserted into the set of alternatives. For the selection of the best solution, 5 criteria were generated, shown in Table 2. The first criterion refers to the average distance traveled by users affected by the disruption (Z). The second criterion (Q_{max}) represents the highest value of the overcapacity ratio in facilities. The third criterion refers to the largest difference in the overcapacity ratio between facilities ($Q_{max} - Q_{min}$), where Q_{min} represents the smallest value of the overcapacity ratio in facilities. The fourth criterion shows the number of facilities in which capacity was exceeded (N^{Q^+}), and the fifth criterion refers to the number of located TFs. It should be noted that all criteria are minimization type. Based on these five criteria, the solution is evaluated, and then the ranking is established.

Type of criteria	**Criteria**				
	Z [km]	Q_{max} [%]	$Q_{max} - Q_{min}$ [%]	N^{Q^+}	Number of TFs
max/min	min	min	min	min	min

Table 2: *Criteria for choosing the best solution using the TOPSIS method.*

Steps of applying the TOPSIS method [13]:

1. Normalization of the initial matrix, where:
   J – set of maximization criteria
   J' – set of minimization criteria
   A – set of all alternatives
   m – number of alternatives
   i – index of alternative
   n – number of criteria
   j – criterion index
   x_{ij} – element of the initial matrix (value of alternative i for criterion j)
   r_{ij} – element of the normalized matrix (normalized value of alternative i for criterion j)

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{k=1}^{m} x_{kj}^2}}, \quad \forall i = 1, \ldots, m, \ \forall j = 1, \ldots, n \tag{15}$$

2. Weighting of the normalized matrix by weights:
   v_{ij} – element of the weighted matrix

$$v_{ij} = w_j \cdot r_{ij}, \quad i = 1, \dots, m, \ j = 1, \dots, n \tag{16}$$

3. Determination of ideal (A^*) and anti-ideal (A^-) solutions:

$$A^* = \left\{ \left(\max_i v_{ij} \mid j \in J \right), \left(\min_i v_{ij} \mid j \in J' \right) \middle| \, i = 1, \dots, m \right\} = \{v_1^*, v_2^*, \dots, v_n^*\} \tag{17}$$

$$A^- = \left\{ \left(\min_i v_{ij} \mid j \in J \right), \left(\max_i v_{ij} \mid j \in J' \right) \middle| \, i = 1, \dots, m \right\} = \{v_1^-, v_2^-, \dots, v_n^-\} \tag{18}$$

4. Determining the distance of alternatives from the ideal (S^*) and anti-ideal (S^-) solutions:

$$S_i^* = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^*\right)^2}, \quad i = 1, \dots, m \tag{19}$$

$$S_i^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^-\right)^2}, \quad i = 1, \dots, m \tag{20}$$

5. Calculating the relative closeness of alternatives to the ideal solution (C_i^*):

$$C_i^* = \frac{S_i^-}{S_i^* + S_i^-}, \quad i = 1, \dots, m \tag{21}$$

6. Rank the alternatives according to their C_i^* values. C_i^* values range from 0 to 1. An alternative that has a C_i^* value closer to 1 should be ranked higher. In other words, the alternatives should be ranked from the highest to the lowest C_i^* value.

The EA-TOPSIS approach is applied to analyze the obtained solutions and to identify the best one from both user and system perspectives.

3. Computational study

The main aim of this study is to develop a universal approach applicable to different real-world systems. The implementation of the proposed approach in a specific system requires the definition of additional criteria by domain experts, as these may vary depending on the system's characteristics and priorities. For this reason, the testing in this study is conducted on hypothetical instances and relies on a fundamental set of criteria relevant to any practical setting. This enables the evaluation of the methodological properties of the approach while preserving its general applicability.

The hypothetical example covers a territory with 20 demand nodes (municipalities), where 2,000 users live. Users are aggregated into demand nodes so that each node has 100 users. The distances used in the model are calculated according to the Euclidean distance based on the (x, y) coordinates of the demand nodes shown in Table 3. In the observed hypothetical example, there are 5 permanent facilities whose locations are shown in Figure 2 (nodes 1, 5, 9, 13, and 17). The locations of the PFs and the distribution of users they serve according to the territorial division are shown in Figure 2.

Under normal operating conditions of the system, users must respect the territorial division, i.e., each user is preassigned to exactly one PF. There are 20 demand nodes (municipalities) in the system. The PF is located in 5 municipalities and serves users from the region to which it belongs. The capacity of PFs is defined based on the number of users who gravitate towards it, i.e., in this example, the capacity of each PF is 400. The remaining 15 municipalities in which there is no PF represent potential locations for locating TFs in the case of a disruption. TF can be located next to facilities of a similar purpose in the selected municipality, which facilitates the establishment of TF due to the proximity of trained personnel, equipment, and other necessary resources for the operation of TFs. In this example, the capacity of TFs is defined as 50 % of the capacity of PFs (TFs capacity is 200).

Demand node	**(x, y)**	**Demand node**	**(x, y)**	**Demand node**	**(x, y)**	**Demand node**	**(x, y)**
1	(20, 80)	6	(60, 70)	11	(98, 90)	16	(45, 20)
2	(10, 70)	7	(45, 55)	12	(106, 65)	17	(85, 18)
3	(12, 90)	8	(42, 80)	13	(25, 30)	18	(69, 8)
4	(22, 95)	9	(73, 73)	14	(15, 10)	19	(67, 30)
5	(60, 70)	10	(94, 65)	15	(10, 40)	20	(102, 25)

Table 3: *Coordinates (x, y) of the demand nodes.*

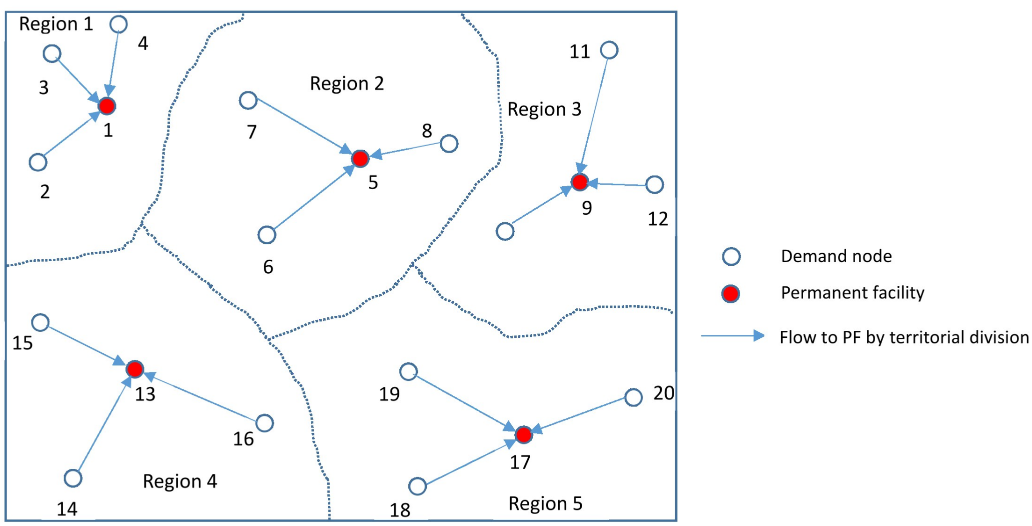


Figure 2: *The territorial division of the demand nodes by PFs and the potential location for TFs.*

To solve the proposed capacitated p-median model, we used ILOG CPLEX 12.1 on a 64-bit ACER computer with an Intel(R) Core (TM) i5 2.50 GHz processor and 8 GB of RAM. Python version 3.10.9 was used in Spyder environment version 5.4.5 to process data and search for solutions.

The model was tested for different variants of attacks on PF and TF locations. In all tested examples, a unique solution was obtained by applying the EA approach. Based on this, it can be concluded that the number of alternatives is equal to the available number of TF that can be located, increased by one (for the case when the temporary facilities are not located, i.e., $p = 0$). Due to the scope of the paper, an example of an attack on two PFs (1 and 5) is shown and explained in detail. The results of testing the developed approach in the case of an attack on PFs (1 and 5) are shown in Table 4 and illustrated in Figure 3. Table 4 shows the solutions obtained in 4 different situations, i.e., solutions obtained depending on the number of located

TFs (from 0 to 3). Column three shows the locations of the TFs. NAU denotes the number of users affected by the disruption in the case of an attack on PFs (1 and 5), and NAU is equal to 800 users in each scenario. Z denotes the value of the objective function, i.e., the average distance traveled by users affected by the disruption.

The total distance that users travel under normal conditions to obtain the requested service is 27,118 km, with the average distance traveled by users being 13.6 km. The disruption caused by the attack on two PFs (1 and 5) affected users in 8 demand nodes (1, 2, 3, 4, 5, 6, 7, and 8). In the event of an attack on the aforementioned two PFs, it is necessary to introduce 3 TFs so that users do not feel the consequences of the disruption in terms of traveled distance. In the scenario in which 3 TFs are introduced, the average distance traveled is 11.8 km, which is 1.8 km less than in normal conditions. Based on this, it can be concluded that in this example, by introducing 3 TFs, users would not feel the consequences of the disruption, from the perspective of the traveled distance. It can also be concluded that in this example, no more than 3 TFs should be located because locating more than 3 TFs would lead to unnecessary costs.

The highest value for $Z = 45.1$ km is obtained in the first scenario when zero TFs are located. In the case of locating only one TF, the value of Z decreases from 45.1 km to 30.8 km. In this scenario, it is best to locate the PF in Municipality 3. When locating two TFs, the objective function value is 17 km. The lowest value of the objective function is achieved by locating three TFs, with $Z = 11.8$ km.

Number of TFs	**Attacked PFs**	**Location of TFs**	$\boldsymbol{NAU}$	$\boldsymbol{Z}$
0		/		45.1
1	1 and 5	3	800	30.8
2		3 and 7		17.0
3		2, 4, and 6		11.8

Table 4: *Test results given by the EA approach in the case of the attack on the two PFs.*

Figure 3 shows the solutions in the case of attacking two PFs (1 and 5) and locating 0 TFs (Figure 3a), 1 TF (Figure 3b), 2 TFs (Figure 3c), and 3 TFs (Figure 3d). For each of the four TFs location variants, the redistribution of users from the 8 demand nodes affected by the attack on PFs 1 and 5 is shown. In the first example (Figure 3a), generating a redistribution plan without introducing temporary facilities is not possible due to capacity constraints (7)-(10). Figure 3a shows a user redistribution plan assuming that each user is served by the nearest active facility. According to the redistribution plan shown in Figure 3a, overcapacity in some facilities is 150%. This is proof that when generating a redistribution plan, it is necessary to take into account the facilities' capacities, which was done in the mathematical formulation proposed in this paper. Given that the attack on two PFs affected 800 users (45% of the total number of users in the system), PF and TF facilities must allow overcapacity in that ratio so that all users can be served ($\rho = 0.45$). Due to the constraints of the permitted overcapacity ratio of facilities to 45% and the difference in overcapacity ratio between facilities of 10% ($\beta = 0.1$), users from certain nodes have been redistributed to multiple facilities. The stated constraints are intended to ensure an even load on the active (non-closed) facilities. In Figures 3b, 3c, and 3d, the redistribution plan is defined respecting the capacity constraints. From the presented solutions, it can be seen that in the case of the introduction of 1 TF (Figure 3b), users from all regions feel the consequences of the disruption. In the case of the introduction of 2 TFs (Figure 3c), users from one region do not feel the consequences of the disruption, while in the case of the introduction of 3 TFs (Figure 3d), users from 2 out of 5 regions do not feel the consequences of the disruption. Of the four considered solutions, the solution of the introduction of three TFs (2, 4, and 6) provides minimal consequences for users after a disruption, but the highest cost for the system.

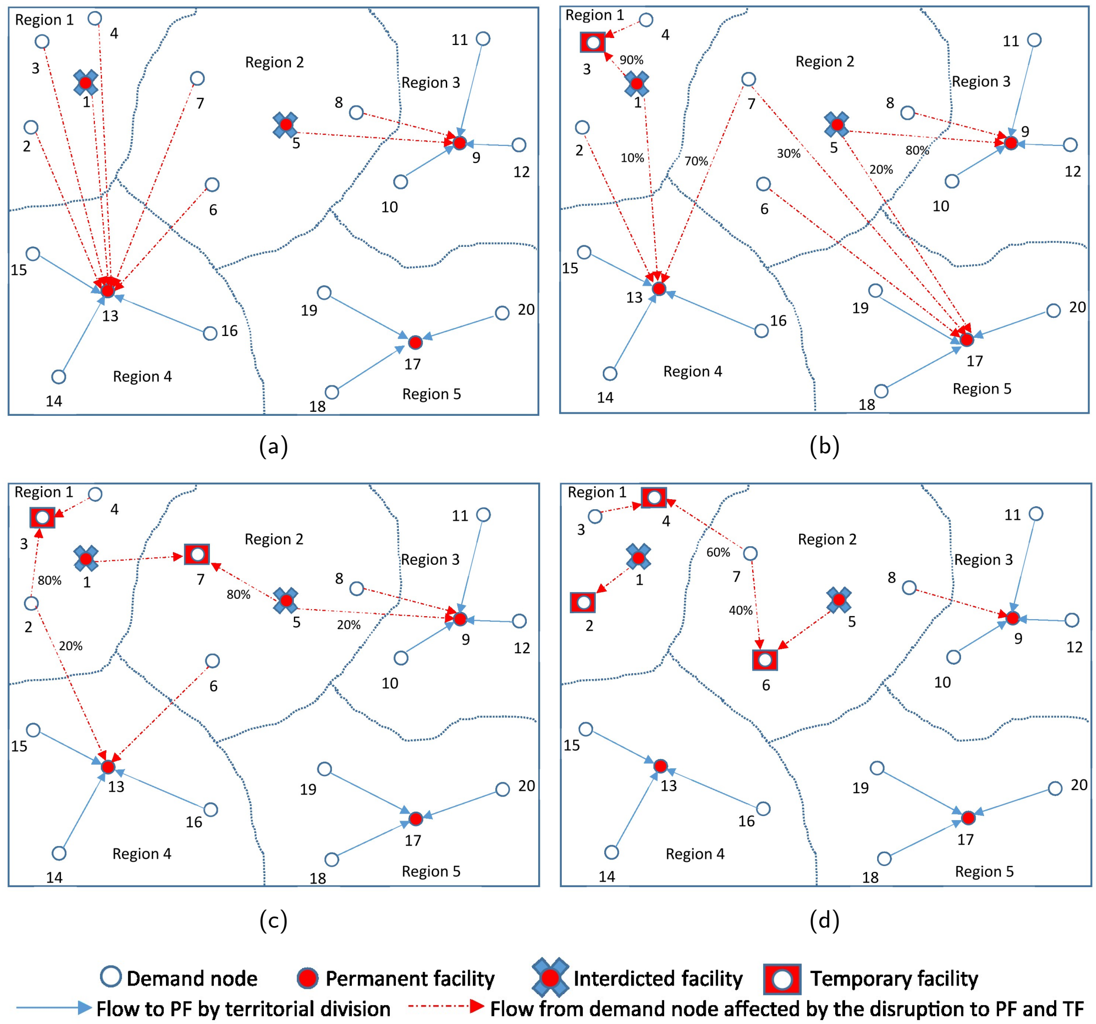


Figure 3: *Examples of attacks of two PFs and redistribution of users in case of location: a) zero TF; b) one TF; c) two TFs; d) three TFs*

To obtain the final solution of the considered problem, it is necessary to select the best scenario, i.e., the number of located TFs. The selection of the best solution can be performed either through expert analysis of the results or by applying the MADM method. In order to select the best solution, it is proposed to combine the exact approach for generating high-quality feasible solutions and the TOPSIS method for selecting the best solution. We call this approach EA-TOPSIS. The EA-TOPSIS method was developed in order to reduce subjectivity in selecting the best solution as much as possible. The input data required for applying the EA-TOPSIS approach to select the final solution in the case of an attack on the PF 1 and 5 are shown in Table 5. Table 5 shows the solutions obtained in 3 different situations (3 alternatives), that is, the solutions obtained depending on the number of located TFs (from 1 to 3). For the scenario where there are no temporary facilities (TF=0), the exact approach provides an infeasible solution and therefore cannot be included in the set of alternatives. The second to sixth columns in Table 5 show the criteria for choosing the best solution, which are explained in detail in Section 2.3. The last row of Table 5 shows the weighting coefficients that define the importance of each of the criteria.

The weighting coefficients were obtained by applying the DR method. When applying this method, the decision maker has a fixed number of points available, in this case, 100. Changing (correcting) the number of points assigned to one of the criteria is reflected in changing the number of points assigned to one or more of the others, i.e., their redistribution is carried out. The average distance (Z) traveled by users affected by the disruption is assigned the highest weight (40), indicating that it is the most important criterion. The number of located TFs is the second most important criterion. The criteria related to overcapacity ratio in facilities (the highest overcapacity ratio (Q_{max}) and the difference between the highest and lowest overcapacity values ($Q_{max} - Q_{min}$)) are in third place in importance. The least important criterion is the number of facilities in which capacity has been exceeded. The values assigned to the weight coefficients need to be normalized. The normalization of the weight coefficient values was performed using the following formula:

$$w_j = \frac{W_j}{\sum_{j=1}^{n} W_j}, \quad \forall j \in J \cup J' \tag{22}$$

W_j weighting coefficient of criterion $j \in J \cup J'$
w_j normalized weighting coefficient of criterion $j \in J \cup J'$

In Table 5, the last two columns show the output results obtained by the TOPSIS method. C_i^* represents the relative closeness of alternatives to the ideal solution, based on which the alternatives are ranked. The last column shows the obtained rank of alternatives, which indicates that the best solution is the location of 2 TFs in the Municipality 3 and 7. The EA-TOPSIS approach shows that locating TFs in these municipalities achieves the best balance between the number of located TFs and the average distance traveled by users affected by the disruption. The application of the EA-TOPSIS approach reduces the average traveled distance of the users by 28.1 km and the maximum overcapacity ratio in facilities from 150% to 40%, compared to the case without TFs location. Under normal operating conditions of the system, users travel on average only 3.4 km less to get the service. Respecting facility overcapacity limits and balancing in overcapacity prevents overloading of facilities in the system and ensures efficient and sustainable operation of the system. The solution generated by applying the developed EA-TOPSIS approach is directly applicable in practice. The developed method has the possibility of application in various systems in which there are disruptions in the operation of facilities (system of health facilities, system of police station facilities, system with several warehouses, system of facilities for water supply, etc.).

Input						**Output**	
Alternatives	**Criteria**					**Results**	
	Z **[km]**	Q_{max} **[%]**	$Q_{max} - Q_{min}$ **[%]**	N^{Q^+}	**Number of THs**	C_i^*	**Rank**
1	30.8	45	7.5	4	1	0.39	3
2	**17.0**	**40**	**10**	**4**	**2**	**0.64**	**1**
3	11.8	30	10	3	3	0.61	2
max/min		min	min	min	min		
W_i	40	15	15	5	25		

Table 5: *The values of solutions per criteria and the final rank.*

Sensitivity analysis of the weight coefficients was conducted to evaluate the robustness of the obtained ranking. For each criterion, the weight was independently increased and decreased within the interval of -20% to $+20\%$. The weights were determined using the DR method, where the total sum equals 100. When a weight was changed, the remaining weights W_j $(j \neq k)$

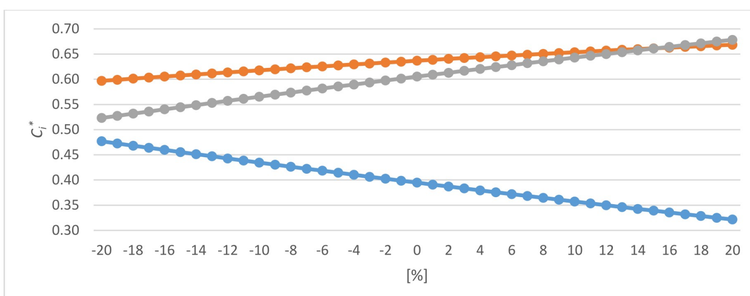
were rescaled proportionally according to their original values to preserve the total sum. This was achieved using the following formula.

$$W'_j = (100 - W'_k)\frac{W_j}{\sum_{\substack{j\in J\cup J'\\ j\neq k}} W_j}, \quad \forall j \in J \cup J',\ j \neq k \tag{23}$$

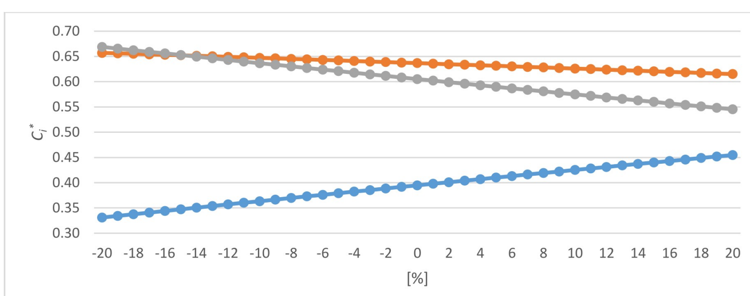
W'_k weight of criterion k after being changed by a specified percentage

W'_j $(j = 1, \ldots, n;\ j \neq k)$ weights of the remaining criteria adjusted proportionally to reflect the change in W_k

No rank reversal was observed for W_2, W_3, and W_4 throughout the perturbation interval. Rank changes occurred only for W_1 and W_5. As shown in Figure 4, the sensitivity analysis for these two criteria is illustrated separately. Changes in the relative closeness of alternatives C_i^* for different values of W_1 are presented in Figure 4a, and for W_5 in Figure 4b. For W_1, the ranking remained unchanged for variations from -20% to $+15\%$, and for W_5 from -15% to $+20\%$. Changes occurred only outside of these ranges. An increase of W_1 by 16% or more results in Alternative 3 becoming the top-ranked solution. Whereas a decrease of W_5 by 16% or more leads to a rank reversal between Alternatives 2 and 3. Since these changes occur only under relatively large deviations in weight, the adopted weight structure can be considered robust, and the resulting decision stable.



(a)



(b)

A1 A2 A3

Figure 4: *Sensitivity analysis of the relative closeness of alternatives (C_i^*) with respect to weight variations (-20% to $+20\%$): a) W_1; b) W_5.*

4. Conclusion

In recent years, disruptions, such as the emergence of viruses, terrorist attacks, or earthquakes, have become increasingly frequent. Such events may interrupt the functioning of systems consisting of multiple facilities to which users are allocated, highlighting the need for models that ensure the system's operation in conditions of disruptions.

This paper discusses the problem of determining the location of temporary facilities and the redistribution of users to permanent and temporary facilities after disruptions. A mathematical formulation is proposed for this problem. In order to determine the final number of located TFs, the TOPSIS method was applied in combination with the exact approach. For the application of the TOPSIS method, 5 criteria were selected based on which the best solution from the set of solutions is selected. One criterion refers to the average traveled distance of users affected by the disruption, three criteria refer to the overcapacity ratio and balancing of the overcapacity ratio in PF and TF, and one criterion refers to the number of located TFs. The solution obtained by applying the EA-TOPSIS approach achieves a balance between the goals of system management and users.

The proposed EA-TOPSIS approach is tested on a hypothetical example of 20 demand nodes and 5 PFs. The model was validated by testing against different variants of PF attacks and by locating different numbers of TFs. The paper highlights an example of an attack on two PFs and locations from 0 to 3 TFs. Locating TF can achieve great savings in terms of the average distance traveled by users. In the analyzed example, it can be reduced by 31.7% by introducing one TF, or even 62.3% by introducing 3 TFs, compared to the case when no TFs are introduced. Also, the capacity constraints in the mathematical formulation ensure a more even redistribution of users. Without capacity constraints in facilities, the overcapacity ratio can reach up to 150%, while with capacity constraints, the overcapacity ratio is limited to 45%.

Overcapacity enables the service of affected users by allowing both TFs and PFs to adapt to increased demand, with capacity allowed to be exceeded up to a predefined ratio. Balancing the overcapacity ratio across facilities distributes users more evenly, preventing extreme overload at individual sites and supporting a more efficient and sustainable system operation under disruption conditions. The capacity constraints enable the direct application of the developed approach. The proposed approach is flexible and can be adapted to specific systems by incorporating additional criteria.

The study also has some limitations. The computational experiments were performed on small-sized instances rather than real-world cases. Furthermore, the approach involves a degree of subjectivity in the selection of the MADM method, the evaluation criteria, and their weights. Additional limitations may arise from the problem size that can be solved exactly using optimization software, such as CPLEX.

Overall, the study provides a theoretical contribution by integrating an exact approach with the TOPSIS method for multi-criteria decision-making under disruption. It further offers practical implications through a flexible framework that supports system managers in enhancing operational resilience.

There are several possible directions for future research, such as: testing the proposed solution approach on real examples (for example, in the case of disruptions in the healthcare system), including additional constraints and criteria (for example, available budget and the cost of locating temporary facilities), applying other MADM techniques, defining the number of temporary facilities that need to be located using fuzzy logic systems or some artificial intelligence methods.

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