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Research Article

Prioritization of Bridges to Improve Emergency Road Network Performance after the Earthquake

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Following an earthquake, the issue of relief, mainly in metropolises, where the extent and depth of the devastation can be widespread, is crucial. Meanwhile, urban roads including the bridges as major arteries play an essential role after the earthquake. Bridges also have a unique role in making disaster response routes network efficient. Therefore, it is necessary to ensure their full performance in disasters such as earthquakes. On the other hand, maintaining this function for all bridges in a network requires huge costs, which is generally impossible. This study aims to assess the selection and prioritization of bridges for retrofitting according to their importance and role in helping disaster response routes network. In this paper, to prioritize bridges in an emergency road network, a five-stage methodology is presented using analytical methods and an optimization model. Given the importance of network length and critical points connectivity in the efficiency of the emergency road network, the probability of failure, network length, and travel time have been used as major indicators in prioritizing bridges for retrofit funding, especially in the first 72 hours after the disaster. This methodology has also provided the possibility of evaluating budget allocation options. The results are presented for the Sioux Falls model, and the efficiency of the proposed model has been shown.

1. Introduction

A high-intensity earthquake in a large and densely populated city can cause a massive humanitarian disaster. In such cases, even less severe earthquakes may lead to extensive damages [1]. Lack of proper access to disaster relief centres in the city (spatially and temporally) is one of the most important causes of human disasters This lack of access can be seen when damage to all or a section of the road network makes efficient use of the remaining network impossible [2–4]. Rescue and relief missions are difficult due to earthquake-induced chaos, road network use for city clearance, and uncoordinated public assistance. An earthquake catastrophe usually leads to secondary disaster in most observations, which may incur some additional difficulties to rescuing. These disasters may cause unthinkable outcomes and leave us no time to respond [5]. Since the entire network of urban streets cannot be managed after the earthquake, it is necessary to implement this, at least along the streets (which creates the greatest amount of coverage between important population points and rescue centres in the city). Also, considering the importance of controlling and managing the emergency road network (ERN) in times of disaster, these passages must be protected from damage and can be used at any time.

Bridges located on the ERN have always been one of the most vulnerable components of the transportation network, and therefore, before the disaster occurs, they should be ensured. For this purpose, it is essential to investigate and prioritize bridges located in urban street networks to provide access through the ERN. This paper has tried to provide a method of prioritizing bridges for retrofitting according to the city's need for emergency roads.

The rest of the paper consists of five sections. After this precedence, Section 2 is devoted to reviewing the literature. A model for prioritizing the bridges of the ERN is demonstrated in Section 3. In Section 4, a case study on the Sioux Falls network is presented, and finally, in the last section, the conclusions are manifested.

2. Literature Review

Given that this paper's subject is focused on prioritizing bridges to enhance the performance of the emergency road network, this section discusses the related issues of disaster network design problems and bridge prioritization. Additionally, it is remarkable that some models consider only ranking methods when solving prioritization problems, whereas others consider resource allocation as well. As a result, this section discusses three topics: designing an emergency road network, ranking links and bridges, and allocating budget resources.

2.1. Emergency Road Network Design. The basis of the emergency road network design is the identification of emergency routes, which is critical and necessary in densely populated cities following an earthquake. In this regard, Shariat et al. [6] have presented the quickest approach to access emergency routes for relief forces. Furthermore, Viswanath et al. [7] assessed the multicommodity maximal covering network design problem to plan emergency routes that reduce travel time between demand pairs while maximizing the population covered by these routes. They also provided a set of responses to choose decision-makers (DMs). Shariat et al. [8] describe a goal programming (GP) approach for identifying emergency routes that minimize travel time while increasing coverage. The optimal route identification approach proposed by Nikoo et al. [9] incorporates three distinct elements: length, travel time, and the number of routes. By utilizing these elements, Nikoo et al. [9] introduce a hybrid multiobjective method to convert a multiobjective problem into a single-objective form.

Additionally, Babaei et al. [2] incorporate the total time spent on emergency travels, the total network length, and the coverage extent to emergency demand/supply points into a multiobjective integer linear programming model. The most recent paper in this field, Nikoo et al. [10], suggests a large-scale emergency network design problem considering earthquake scenarios in the metropolis of Tehran. Given the model's limitations, the main factor in this study was minimizing total network length. Finally, based on the aforementioned research and the similarity of this study's network, the total length would be regarded as the most important performance factor when designing an emergency road network. It is noteworthy that the network length index must be regarded as a high priority to manage, reopen, and maintain the established routes appropriately. In the development of our model, we chose decision factors that are commonly used in the design of emergency road networks in a variety of situations based on the literature review.

2.2. Rankings of Links and Bridges. Retrofitting transportation facilities such as transportation routes has always been acknowledged as a key aspect of network design to prevent earthquake damage when ranking links and bridges [11]. In this regard, Du et al. [12] show the budget constraints as a notable limitation in upgrading the links. They also present a road network prioritization method using the link importance index. Besides, Yin et al. [13] examine the uncertainty in demand and budgetary constraints. They have evaluated a problem to determine which network links require upgrading (capacity increase) and how much funding should be allocated to maximize the two indicators of the system's efficiency (travel time and stability). In addition, the appropriate investment allocations by specifying critical links, increasing storage capacity, and proposing constraints in a vulnerable network have been assessed by Chen et al. [14]. Poorzahedi et al. [15] suggest a model, that is, upgrading the network by improving the links. After determining the importance of each link in this paper, investment prioritization was determined using the consumer reliability excess. Asakura et al. [16] choose a set of investment patterns for the links in order to achieve the highest level of performance reliability under uncertain conditions. Song et al. [17] present a model for selecting the major components of network retrofitting using an optimization and simulation process. The budget is considered a constraint in this model, which was implemented in the South Korean city of Ulsan, and the number of people killed is regarded as the objective function. The importance of road transportation networks is evaluated and ranked in the study of Ukkusuri and Yushimito [18] through an innovative process based on travel time performance.

2.3. Allocation of Budget Resources. Transportation network links and critical routes have been identified and investigated in the allocation of budget resources, taking postdisaster performance indicators into account.

Peeta et al. [19] examine the structural relationship between network retrofitting components and the resistance capability of infrastructure networks in the face of disaster. This study identified the links in demand for retrofitting using the performance indicators of accessibility and travel time. A two-level model with its approximate solving procedure was then presented and solved for two modes in Istanbul city (one for 25 nodes and 30 links and the other for eight nodes and 9 links). The link investment has been identified at the first level, and the travel time between origin-destination pairs has been minimized at the second level.

Shariat et al. [20] explain a resource allocation model to improve connection and travel time reliability under uncertain conditions following natural disasters such as earthquakes. The path links that should be preserved in the event of a disaster are specified in this model, and the reliability indicators are calculated using a Monte Carlo simulation. A genetic algorithm was used to solve the numerical example in this case. Consequently, Shariat et al. [21] suggest the reliability of source-destination connectivity and

travel time as two indicators of network efficiency. The study presents a model for optimal investment in the transportation network to maintain its performance after the accident. Brown et al. [22] present retrofitting options using a multiobjective optimization algorithm after determining network component characteristics in the postdisaster situation and showing the events using optimization and simulation techniques. The model was implemented for the Memphis road network of America.

To allocate resources in vulnerable transportation networks, Shariat et al. [21] have considered functional reliability indicators for link capacity and access of points. They considered the budget resource minimization from the perspective of decision-makers. Maximizing capacity and accessibility were also considered from the perspective of operators. While using the gradient method to solve the nonlinear program, an efficient solution for large-scale problems is suggested for future works. Edrissi et al. [23] evaluate the minimization of damages caused by major earthquakes. The three main parts of their model are the reconstruction of damaged buildings, strengthening of existing transportation infrastructures, and locating and allocation of different first aid levels. The quantitative definition of improved conditions, following the coordination of different aspects in disaster phases, is one of the most important findings of this study. Dehghani Sanj [24] presents an operational and fairly comprehensive model for planning road network maintenance in failure conditions. The study's objective function is designed both linearly and nonlinearly for implementation in large-scale networks. This model was implemented in Istanbul's road network over a one-year and multiyear time frame. Due et al. [3] discuss a bilevel stochastic optimization model for determining the links during the retrofitting process. In this model, two types of uncertainties (in the disaster characteristics or survival network related to each disaster) are considered seamlessly. Because of the model's complexity, the problem has been divided into two linear programming models and the shortest path. The problem was then solved using an innovative two-step algorithm. They also tested their model with a numerical example.

2.4. Research Gap. Several studies such as Nagae et al. [11], Faturechi and Miller-Hooks [25], Fan and Liu [26], Yueyue et al. [27], Nielsen et al. [28], Brown et al. [22], Zhang [29], Sohn [30], Faturechi and Miller-Hooks [31], and Edrissi et al. [32] have presented various models in prioritizing and retrofitting the components of the transportation networks. Unlike evacuation routes, which have been discussed in a variety of studies, few articles have directly addressed the emergency road network design problem, such as Babaei et al. [2], Shariat et al. [6], Shariat et al. [8], Viswanath et al. 2003 [7], Nikoo et al. [9], and Nikoo et al. [10]. The prioritization of bridges in the ERN has not been investigated so far, according to the literature review. Given the greater importance of these routes in critical situations following earthquakes and the vulnerability of bridges in road networks, this study proposes a method to prioritize bridges for the first time. This analytical method is proposed using an optimization model considering the disaster response routes.

3. Methodology of Bridges Prioritization in the Emergency Road Network

In this study, the methodology used to rank the bridges includes five steps. Figure 1 briefly presents these steps. Figure 2 depicts the logical path to be taken for the proposed method of prioritizing the bridges retrofitting after an earthquake. As a quick overview of our methodology, we will explain the main components of our proposed model in the following paragraphs. To clarify any ambiguities, the following sections of the paper will characterize each component of the proposed methodology in greater depth. Table 1 contains the notations used throughout the model formulation, such as sets, parameters, and variables, to help better understand the model.

Initially, as shown in Figure 2, the problem is defined after the network has been formed using topological elements such as links, nodes, and so on. This initialization procedure entails the generation of earthquake scenarios in the form of binary sets, each of which illustrates the failure statuses of bridges in the corresponding scenario. Following that, the optimization procedure results in the shortest possible total network length (TNL) in each of these states. Another constraint in our model is the retrofitting budget, which determines the retrofitting cost for each of the failure "states' and offers distinct retrofitting "options." The last step, which offers "expected values" for TNLs, is supplemented by TNLs calculated earlier in the optimization process. The retrofitting options get sorted according to their total failure probability, along with their expected value for TNLs. Finally, as a result of this model, decision-makers would be able to provide the most accessible network with the maximum possible capacity for operators while spending the least amount of resources.

3.1. Step 1: Determination of Possible Road Network Bridge States after an Earthquake. Bridges' seismic vulnerability is expressed using fragility curves and the probability of bridge failure under different earthquake intensities [33]. An earthquake's occurrence probability with specific intensity can also be estimated using different structural engineering techniques and available data.

As with every road network, there are a number of links (including bridges) and nodes. Bridges, as the most crucial network components, are prone to failure in varying degrees (no damage, minor damage, moderate damage, and complete failure). We assumed that if a portion of the bridge is damaged, the bridge will be either usable or unusable, regardless of total damage or blockage of a portion of the bridge. In this study, the postdisaster state of each bridge is regarded as functional or nonfunctional, denoted by 1 or 0, respectively. Based on the constraints of our model, the state of the bridge when a lane is blocked but the rest of the bridge is operational is referred to as the

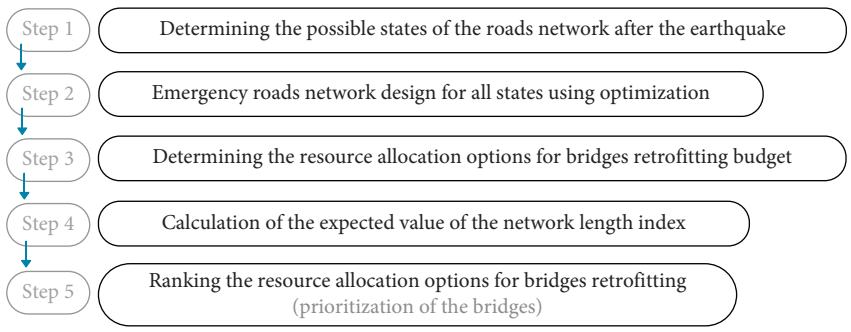

Figure 1: Steps of the suggested bridges prioritization method.

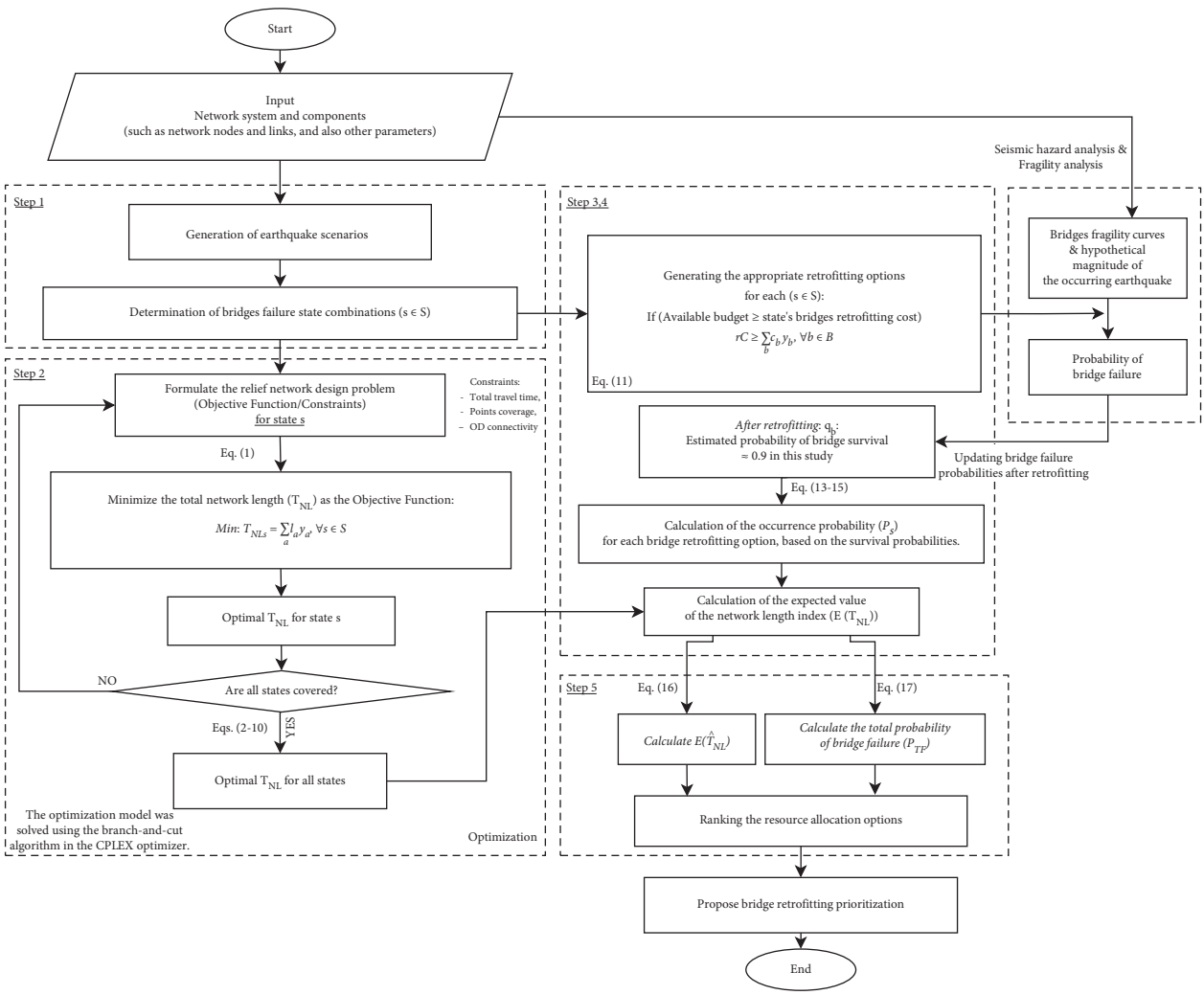

Figure 2: Flowchart of the proposed model for prioritizing bridge retrofits following an earthquake.

functional form (1), and this assumption was used to solve the problem. Thus, based on the number and condition of each bridge's failure, different combinations of the failure states are possible (s). The set of bridge failure state combinations defines the possible states of a road network (1: functional and 0: nonfunctional). For example, in a road network with five bridges, 00000 denotes the state that all the bridges are inoperable, whereas 11111 denotes that all the bridges are operable.

3.2. Step 2: Emergency Road Network Design for All States Using Optimization. In this step, regarding the possible conditions of the previous step, the disaster relief network

Table 1: Notations.

Sets	
S	Set of all possible combinations of bridge failure states, $s \in\in S$
A	Set of all links of the transportation network, $a \in\in A$
K	Set of all points, $k \in\in K$
B	Set of all bridges, $b \in\in B$
R	Set of all routes, r $\in\in R$
OD	Set of all demand pairs (origins and destinations), od $\in$ OD
Parameters	
M_{big}	A large enough positive number
T_r	Travel time of path r
TT	Desired total travel time for a certain network
T_{TT}	Total travel time for a certain network
l_a	Length of link a
I_r	Importance of route r
K_a	Postdisaster capacity of link a
N^{od}	Number of required routes between an origin (O) and destination (D)
q_r^{od}	Amount of demand between the o and d, which crosses from route r
$\propto_o$	Minimum coverage level
rC	The available allocable budget for retrofitting
c_b	Retrofitting cost of bridge b
P_b	Predicted probability of the survival of bridge b before retrofitting
q_b	Estimated probability of survival of bridge b after retrofitting
Variables	
y_a	1 if link a is used, and 0 otherwise
x_r^{od}	1 if path r is used between origin O and destination D, and 0 otherwise
z_k^o	1 if point k with type O is covered, and 0 otherwise
δ_r^a	1 if link a is part of path r, and 0 otherwise
δ_a^k	1 if point k is covered with link a, and 0 otherwise
$H_s^b \sim y_b$	1 if bridge b in the state s is nonfunctional, and 0 otherwise

is designed through optimization. In the present study, the performance functions of the disaster response route network have been used to determine the objective function and constraints of the relief network. In the proposed model, the total network length (TNL) is used as the objective function, and the considered constraints are the total travel time, the points coverage, and the origin-destination connectivity. The following sections present the disaster relief network problem considering the objective function and constraints.

3.2.1. Objective Function. Constraints on the use of police forces to control the road network in critical situations and limited resources to meet the expenses of the preparation, maintenance, and retrofitting are among the most important issues in designing relief routes network (notably in metropolises and large cities with long roads network). The total length is the most important performance index, as mentioned in the literature review. The total length minimization of the selected links, known as the TNL, is considered the objective function. In equation (1), l_a represents the length and y_a is the decision variable to choose link a (1 if link a is used, and 0 otherwise). This variable is used to indicate whether or not link "a" is used. If link "a" is used, y_a is set to 1; otherwise, it is set to 0.

The different combinations of the bridge failure states are considered as s. For each state $s \in$S, we must solve and execute equation (1). This is depicted in Figure 1 at Step 2. Model constraints come in the next section.

$$\text{Min: } T_{NLs} = \sum_a l_a y_a, \quad \forall s \in S. \tag{1}$$

3.2.2. Model Constraints. Equations (2)–(10) represent the proposed model constraints. In these constraints, it is possible to define several demand pairs for disaster relief access, each of which has its origin and destination. Routing between the disaster relief access demand point pairs is considered in equations (2) and (3). OD is the set of disaster relief route demand, and $N^{o\,d}$ is the number of required routes between an origin (O) and destination (D). It is essential and a vital issue to create access routes (connections) in crises. Between each demand pair (O and D), there are different possible routes that the model is allowed to choose only a limited number of them. Equation (2) controls the route selection to provide access from the demand point o to the d service provider point. x_r^{od} is the path selection variable, which is binary (0 and 1) and is related to the link selection decision variable (y_a). Considering the additional routes for more important demands, the connection likelihood of demand pairs will increase. If N^{od} is held larger than one, the request for access to relief routes can be distributed between several routes. q_r^{od} is the amount of demand between the o and d, which crosses from route r. If a link is not on the selected network, y_a is 0, and otherwise, it is 1. These equations ensure that each demand gets out of its

origin and reaches the end node after passing through the middle nodes. Equation (3) is the factor connecting the path to the link. Selection of the path r using the δ_r^a parameter (indicating that link a is part of path r) also selects the associated $y_a$variable and turns its value to 1. For each link, the maximum number of passing routes can be considered independently. Equation (3) ensures that the total number of disaster relief access routes on each link a should not be greater than its capacity (q_r^{od}). The points coverage in the network and establishment of a minimum coverage level ($\propto_o$) in the model are the results of equations (4)–(6). y_a selects the used links, whereas δ_a^k selects the points covered by these links. Equations (4) and (5) use these parameters to determine relevant covered points for the used links.

By selecting the $y_a$links, using equations (4) and (5), the covered points of the K set become specified. The decision variable z_k^o is a binary number. If point k with type O (origin) is covered, it will be 1, and otherwise, it will be zero. M_{big} represents a number that is large enough. In fact, by specifying the neighbour matrix by each link through the δ_a^k parameter (indicating that a link covers the k point), the covered points in the model constraints are also specified. When the link "a" covers the point "k," then the corresponding δ_a^k parameter is set to 1.

As the coverage of emergency areas is critical in our model, equation (6) addresses this challenge. In this equation, the minimum coverage level ($\propto_o$) is defined as the ratio of the number of covered points to all coverable points. Some locations coverage of the disaster relief network (not ODs) should also be taken into consideration. In case of the need for imminent coverage, the coverage parameter for that set of points is equal to 1. As the importance of emergency trips varies for different purposes, weighted travel times have been considered for different ODs by using I. For example, trips related to victims are more important than other emergency trips. In the case study, these values are set to the same value (1). Demand pairs (OD) in equations (7) and (8) should be connected via r routes between o and d in less time than the desired total travel time (TT). Equation (8) ensures that T_{TT}, the network's total travel time, does not exceed TT as the desired total travel time. Between each origin and destination (depending on the importance of the covered demand), the category of importance (I_r) is considered and multiplied by the travel time (T_r). The sum of these multiplications in the selected routes must be less than the desired total travel time (TT), which is shown in equation (8). This parameter, as the model's input, is evaluated based on the analysis of the travel time of demands. It is worth noting that T_r reflects the shortest travel time for a single OD pair, but T_{TT} represents the total travel time for a certain network, which is the sum of the T_r of all OD pairs existing in the network. Thus, both T_{TT} and TT are calculated for the network as a whole rather than for a particular link.

In this model, B represents the set of bridges ($b \in B$). Furthermore, equation (9) considers the predetermined state of the bridges. The H_s^b parameter in this equation shows the bridge's failure state, which would be 1 in case of bridge failure. As a result, the mentioned failed bridges that need to be retrofitted would be selected using y_b. It can be concluded that y_b would be considered 1 for selected bridges with failure, and otherwise, it would be 0. Equation (9) determines a particulary_a for each bridge ($b \in B$) based on its failure state in s. The y_b parameter would therefore be employed in equation (11), taking into account candidate bridges for retrofitting.

The general model in this situation is implemented based on the possible conditions s, and the remaining bridges enter into the model through this set of constraints. Finally, equation (10) shows the states of the binary decision variables in the model.

We solve the optimization model of Step 2 using a branch-and-cut deterministic algorithm with a convex solution space. It is worth noting that because the branch-and-cut algorithm is exact, there are no local or global minimums. The branch-and-cut exact algorithms may be used to solve and prove optimality for large integer linear programs [34]. Our model was implemented in Java, and it was solved with the IBM CPLEX optimizer utilizing the branch-and-cut algorithm on a computer with a Quad Core CPU running at 2.1 GHz and 8 GB of RAM.

$$\sum x_r^{od} \geq N^{od}, \quad \forall (o,d) \in OD, \tag{2}$$

$$K_a \cdot y_a \geq \sum_r \delta_r^a \cdot x_r^{od} \cdot q_r^{od}, \quad \forall a \in A,\ r \in R,\ (o,d) \in OD, \tag{3}$$

$$M_{\text{big}} \cdot z_k^o \geq a \sum \delta_a^k \cdot y_a, \quad \forall k \in K,\ a \in A, \tag{4}$$

$$z_k^o \leq \sum_a \delta_a^k \cdot y_a, \quad \forall k \in K,\ a \in A, \tag{5}$$

$$\frac{\sum_k z_k^0}{n_0} \geq \alpha_0, \quad \forall o \varepsilon O,\ k \varepsilon K, \tag{6}$$

$$T_{TT} = \sum_r I_r \cdot T_r x_r^{o\,d}, \quad (o,d) \in OD,\ r \in R, \tag{7}$$

$$T_{TT} \le TT, \tag{8}$$

$$y_b = H_s^b, \quad \forall b \in B,\ s \in S, \tag{9}$$

$$y_b, x_r^{od}, \quad y_a, z_k^o \in 0,1, \forall r \in R, \forall a \in A, \forall k \in K,\ (o,d) \in OD,\ o \in O. \tag{10}$$

3.3. Step 3: Determining the Resource Allocation Options for Bridge Retrofitting. In equations (11) and (12), the possible retrofitting options are evaluated and determined based on the available budget (rC). In these equations, C is the budget needed for retrofitting all bridges budget, while r is the budget's percentage, which is allocable. Besides, c_b is the bridge retrofitting costs. In this step, the obtained answers give a set of appropriate options for the budget allocation. It is also remarkable that bridge retrofitting reduces the occurrence probability significantly.

$$rC \ge \sum_b c_b y_b, \quad \forall b \in B, \tag{11}$$

$$y_b \in 0,1. \tag{12}$$

3.4. Step 4: Calculation of the Expected Value of the Network Length Index. This section describes the calculations of the expected value of the objective function regarding the probability of occurrence for each state. Also, in each retrofitting option, the likelihood of new bridge failure gets updated. In equation (13), q_b is the new probability of bridge survival after retrofitting. Besides, $1 - q_b$ is the survival probability for the other bridges, which were not selected to be retrofitted. Based on the distinct elements of each scenario, the survival probability after retrofitting would be calculated differently. Various elements of a catastrophic scenario would have an impact on this amount. The hypothetical value of 0.9 was used in our earthquake scenarios based on the hypothetical structural quality of the bridges, the hypothetical available budget, and the hypothetical magnitude of the occurring earthquake. There are a variety of other values that we could consider, leading to a variety of other earthquake scenarios. The input variables for the bridge's probability of survival and failure are defined to a decimal place precision. As a result, a value such as 0.9 would be appropriate, which is taken into account in this study for the survival probability after retrofitting.

Equations (13) and (14) are specifying the probability of bridge survival ($f_s(b)$) and the occurrence probability (P_s) in each state s.

Moreover, equation (15) determines the expected value of the TNL ($E(T_{NL})$) regarding the "s" state. T_{NLs} is the objective function's value in state s, knowing that each state s shows a combination of stable and damaged bridges. It is noteworthy that in the sampling method, a set of M states will be selected ($M \subset S$).

$$f_s(b) = \begin{cases} q_b, & \text{if } H_s^b = 1, \quad \forall b \in B,\ s \in S, \\ 1 - q_b, & \text{if } H_s^b = 0, \quad \forall b \in B,\ s \in S, \end{cases} \tag{13}$$

$$P_s = \prod_b f_s(b), \quad \forall b \in B,\ s \in S, \tag{14}$$

$$E\left(T_{NL} = \frac{\sum_{S \varepsilon M} T_{NL_s} \times P}{\sum_{S \varepsilon M} P}\right). \tag{15}$$

3.5. Step 5: Ranking the Resource Allocation Options for Bridge Retrofitting. In bridge ranking, budget allocation options with lower expected values are more desirable. The available budget should also be taken into consideration. Normalized indicators for each state of the network are calculated using equation (16) to compare retrofitting options. In this equation, $(T_{NL})^{\text{Max}}$ and $E(T_{NL})^{\text{Min}}$ are the highest and the lowest TNL, respectively. In each suggested retrofitting option, the total probability of bridge failure is the possibility of simultaneous failure of all bridges. Budget allocation options should have an acceptable total probability of failure to reduce the network vulnerability after the disaster. Therefore, the total probability of bridge failure (P_{TF}) is defined and used to rank the options (see equation (17)). In this regard, $(1 - q_b)$ is the updated value of the bridge failure's probability. Generally, the main goal in the proposed optimization model is to find a budget allocation option with the lowest normalized index value.

$$E\left(\widehat{T}_{NL}\right) = \frac{E(T_{NL}) - E(T_{NL})^{\text{Min}}}{E(T_{NL})^{\text{Max}} - E(T_{NL})^{\text{Min}}}, \tag{16}$$

$$P_{TF} = \prod_b (1 - q_b) \le TF, \quad \forall b \in B. \tag{17}$$

4. Case Study: Sioux Falls Network

For evaluation of the proposed model's performance, the model has been implemented on a well-known network (see Figure 3). We put our methods to the test on a well-tested transportation network, the Sioux Falls network. The mentioned theoretical network, Sioux Falls, has 24 nodes and 38 double-sided links. The 16th, 25th, 28th, 39th, and 41st links are the candidate bridges A, B, C, D, and E in this network. The probabilities of bridge survival and bridge failure before retrofitting and also retrofitting costs are shown in Table 2. Ten demand pairs are

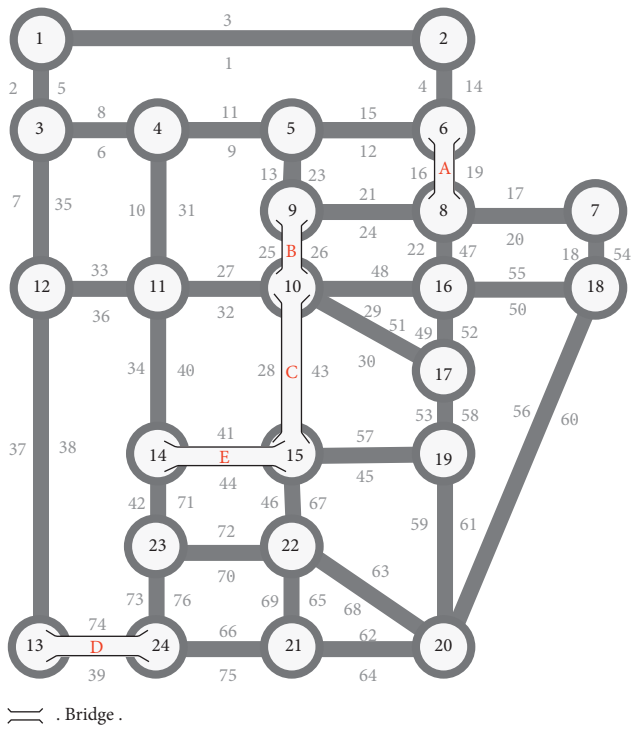

Figure 3: The Sioux Falls network. The candidate bridges are marked with *A*, *B*, *C*, *D*, and *E*.

Table 2: The probability of survival and failure of the candidate bridges.

Bridge name	*A*	*B*	*C*	*D*	*E*
Survival probability	0.7	0.6	0.5	0.4	0.6
Failure probability	0.3	0.4	0.5	0.6	0.4
Retrofitting cost	10	20	30	20	10

examined during this study. The survival and failure probability of the bridges, as well as the costs of retrofitting them, are input variables in our defined model.

Table 2 depicts a set of hypothetical input variable values for a network with five bridges, as illustrated in Figure 3. These data pertain to an earthquake scenario that simplifies the computation of the odds of survival/failure. The earthquake scenario related to Table 2's data was used to test our model. We developed and tested our branch-and-cut algorithm using Java programming in the IBM CPLEX optimizer, which was then used to solve our model and perform our numerical tests on a computer equipped with a Quad Core CPU running at 2.1 GHz and 8 GB of RAM.

4.1. Results

4.1.1. Step 1. Table 3 depicts the possible states of the network. Each bridge can be used or not (1 or 0), giving the network a total of 32 states (25). Each of these states has a chance of occurring depending on the survival/failure probabilities of the bridges without retrofitting. The occurrence probability of each potential condition is computed by multiplying the survival probability of usable bridges by

Table 3: Network possible states and the bridge's failure status after an earthquake.

State number	Bridge failure state 1: usable/0: not usable					Occurrence probability
	A	*B*	*C*	*D*	*E*	
1	0	0	0	0	0	0.0144
2	1	0	0	0	0	0.0336
3	0	1	0	0	0	0.0216
4	0	0	1	0	0	0.0144
5	0	0	0	1	0	0.0096
6	0	0	0	0	1	0.0216
7	1	1	0	0	0	0.0504
8	1	0	1	0	0	0.0336
9	1	0	0	1	0	0.0224
10	1	0	0	0	1	0.0504
11	0	1	1	0	0	0.0216
12	0	1	0	1	0	0.0144
13	0	1	0	0	1	0.0324
14	0	0	1	1	0	0.0096
15	0	0	1	0	1	0.0216
16	0	0	0	1	1	0.0144
17	1	1	1	0	0	0.0504
18	1	1	0	1	0	0.0336
19	1	1	0	0	1	0.0756
20	1	0	1	1	0	0.0224
21	1	0	1	0	1	0.0504
22	1	0	0	1	1	0.0336
23	0	1	1	1	0	0.0144
24	0	1	1	0	1	0.0324
25	0	1	0	1	1	0.0216
26	0	0	1	1	1	0.0144
27	1	1	1	1	0	0.0336
28	1	1	1	0	1	0.0756
29	1	1	0	1	1	0.0504
30	1	0	1	1	1	0.0336
31	0	1	1	1	1	0.0216
32	1	1	1	1	1	0.0504
Sum						1

the failure probability of unusable bridges (see rows one and two in Table 2), and the resulting value is given in the occurrence probability column. In state 31, for example, the occurrence probability is calculated by multiplying the failure probability of bridge A (0.3) by the survival probability of the remaining bridges ($0.6 * 0.5 * 0.4 * 0.6$), yielding 0.0216 (see Table 3). Clearly, the total occurrence probabilities of all states add up to 1.

4.1.2. Step 2. A network with five bridges can have 32 unique configurations because each bridge can be used (1) or not (0). In this scenario, Table 3 shows the 32 alternative bridge states that will be generated in the event of an earthquake. With 32 states being represented in this phase, the relief network design challenge was solved, and the TNL was computed for each state. Table 4 displays the TNL value for each of these 32 states. In the model's constraints, the minimum coverage level is 0.5 ($\propto_o = 0.5$), and the importance category parameter (I_r) is determined based on demand pairs following the disaster.

Table 4: Objective function value results for all possible states in the network.

State number	Total network length (km)
1	114.954
2	114.954
3	111.62
4	123.284
5	118.286
6	123.284
7	111.622
8	116.62
9	118.286
10	123.284
11	119.952
12	116.62
13	119.952
14	126.616
15	124.95
16	126.616
17	116.62
18	114.954
19	119.952
20	119.952
21	118.286
22	126.616
23	123.284
24	121.618
25	123.284
26	128.282
27	119.952
28	118.286
29	123.284
30	121.618
31	124.95
32	121.618

4.1.3. Step 3. In this step, the set of budget allocation options is specified. The terms "option" and "state" are different. An option represents a resource allocation strategy, whereas each state ($s \in S$) represents the postearthquake structural condition of the bridges. S includes all different combinations of bridge failure states. The 5 bridges in the sample network have 32 retrofitting options, with 90 units of available budget needed for retrofitting all bridges(C), which is shown in Table 5. The retrofitted bridges are represented in grey colour. For instance, if the available budget is assumed to be 50 units ($rC = 50$, $r = 0.55$), 5 options from Table 5 become settled. These are A12 to A16, as shown in Table 6.

4.1.4. Step 4. For each option's retrofitted bridges mentioned in the previous step, the survival probability after retrofitting (q_b) is assumed to be 0.9. Afterwards, the occurrence probability (P_s) gets updated for all states, and the expected value of the TNL is calculated. Table 6 shows the obtained results.

4.1.5. Step 5. To analyze the results, we compared the retrofitting options using the proposed method and rank them based on the calculated expected values of TNLs. As a result, A13 with the lowest expected value would be the favoured option. Also, Table 7 shows the ranking, and the output is presented in Figure 4. In terms of TNLs, the A13 option reveals that bridges B and C are given a higher priority for retrofitting than the other bridges (A, D, and E). In this schematic form, relief routes and the bridges requiring retrofitting are represented in yellow colour. Figure 4 also shows that two bridges, B and C, are retrofitted.

For different amounts of the allocated budget from 0 to 90 units, different retrofitting states are presented in Table 8, and the results have been evaluated in the following. In this study, the cutoff value for the total probability of bridge failure (TF) was assumed to be 0.02 ($0 \leq 0.02$). As a result, 16 of the 32 choices had a value less than 0.02, represented in Table 8. Retrofitting options are ranked based on the normalized values of the TNL. The A7 option, with 60 units of the allocated budget, is the best retrofitting option as it has the lowest expected value. Thus, the A7 option, with 60 units of cost, performs better than the A1 option, with 90 budget units with (33% reduction in cost). Having a better network at a lower cost ensures the effectiveness of the proposed method. This result indicates the effectiveness of the proposed method.

4.2. Discussion. This research presents a comprehensive perspective on how to address ERN problems while taking into account a variety of elements at the same time.

Before this analysis, there had not been a detailed investigation of the prioritizing of bridges in the ERN. Given the heightened importance of these routes in critical situations following earthquakes and the vulnerability of bridges in road networks, this study offered a strategy to prioritize bridges for the first time. This analytical method is proposed based on an optimization model that takes the disaster response routes into consideration.

Looking at the findings gives us a better idea of the benefits of the presented method in solving ERN problems. ERN problem-solving is not a one-shot prospect; the results of this study reveal that inventive retrofitting solutions exist, regardless of the budget allocation limitations. The retrofitting solutions that resulted from our model demonstrate that even with tight budgets, an ERN could be adequately retrofitted.

The results of our model clearly show that there is a variety of retrofitting alternatives that require fewer bridges to be retrofitted without raising the total probability of failure or affecting normalized expected TNL. This model may therefore offer options that require less retrofitting while still being as efficient as the alternatives, even if a limited budget is available. Table 7 might be used as an example to illustrate this point. Despite the fact that the A13 option proposes the retrofitting of two bridges, it has a lower expected value than other alternatives that propose the retrofitting of additional bridges.

The fact that this model could provide solutions as effective as we want in the minimal budgets available is another aspect that is being noticed. Table 8 serves as another excellent illustration of this point in the discussion. The "A7" option

Table 5: Retrofitting options.

Number of the retrofitted bridges	Retrofitted bridges					Available budget	Budget allocation option
5	*A*	*B*	*C*	*D*	*E*	90	*A*1
4	*A*	*B*	*C*	*D*		80	*A*2
4		*B*	*C*	*D*	*E*		*A*3
4	*A*	*B*	*C*		*E*		*A*4
4	*A*		*C*	*D*	*E*	70	*A*5
3		*B*	*C*	*D*			*A*6
3	*A*	*B*	*C*				*A*7
3			*C*	*D*	*E*		*A*8
3	*A*		*C*	*D*		60	*A*9
3		*B*	*C*		*E*		*A*10
4	*A*	*B*		*D*	*E*		*A*11
3	*A*	*B*		*D*			*A*12
2		*B*	*C*				*A*13
3	*A*		*C*		*E*	50	*A*14
3		*B*		*D*	*E*		*A*15
2			*C*	*D*			*A*16
3	*A*	*B*			*E*		*A*17
2	*A*		*C*				*A*18
2		*B*		*D*		40	*A*19
2			*C*		*E*		*A*20
3	*A*			*D*	*E*		*A*21
1			*C*				*A*22
2	*A*	*B*					*A*23
2	*A*			*D*		30	*A*24
2				*D*	*E*		*A*25
2		*B*			*E*		*A*26
2	*A*				*E*		*A*27
1		*B*				20	*A*28
1				*D*			*A*29
1	*A*					10	*A*30
1					*E*		*A*31
0						0	*A*32

Table 6: Results of Step 4.

Retrofitting option	Allocated budget	Number of the retrofitted bridges	The expected value of the TNL
*A*12	50	3	120.50
*A*13	50	2	119.88
*A*14	50	3	120.11
*A*15	50	3	122.35
*A*16	50	2	121.92

Table 7: Results of Step 5.

Ranking	Retrofitting option	Allocated budget
1	*A*13	50
2	*A*14	50
3	*A*12	50
4	*A*16	50
5	*A*15	50

comes with a budget of 60 units and has a desirable overall failure probability and also the lowest normalized expected TNL. There are several good solutions in Table 8; however, with a limited budget on hand, the A7 solution is preferred. With 60 units of budget, the A7 solution will outperform the A1 solution, which has a considerably higher budget. Clearly, this strategy is advantageous since it provides not only the same but also superior retrofitting possibilities when compared to alternatives with more retrofitting. When it comes to retrofitting bridges, the choice with the most retrofitting bridges is not necessarily the best option. This indicates the significance of our proposed method.

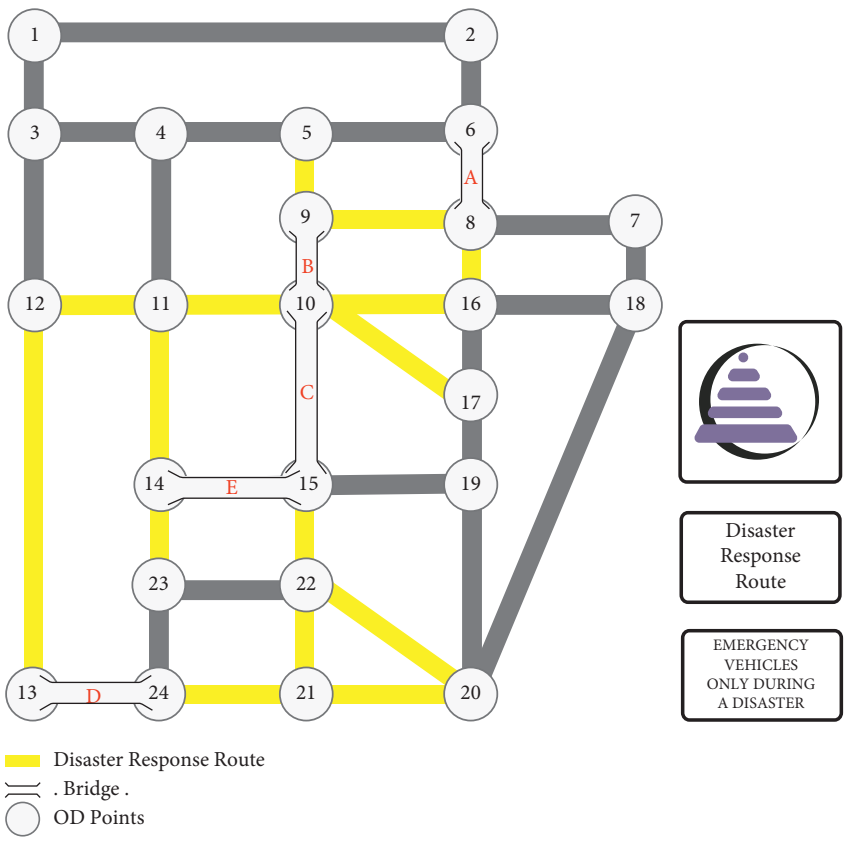

Figure 4: Bridges requiring retrofitting and disaster response routes network.

Table 8: Normalized values for retrofitting options.

Retrofitting option	Allocated budget	$\mathbf{E}(\widehat{\mathbf{T}}_{\mathbf{NL}})$	$\mathbf{P}_{\mathbf{TF}}$
$A1$	90	0.662	$p \leq 0.001$
$A2$	80	0.495	0.002
$A3$	80	0.820	0.001
$A4$	70	0.263	0.003
$A5$	70	0.707	0.002
$A6$	70	0.656	0.008
$A7$	60	0.096	0.016
$A8$	60	0.908	0.008
$A9$	60	0.540	0.010
$A10$	60	0.421	0.012
$A11$	60	0.755	0.003
$A12$	50	0.402	0.013
$A14$	50	0.309	0.016
$A15$	50	0.846	0.010
$A17$	40	0.356	0.020
$A21$	40	0.886	0.013

Finally, another advantage of this model is that it allows for both the prioritization of bridges and the integration of network architecture in the same model at the same time. This prioritization is not separate from the designation, and because it presents a range of options to decision-makers, it would make it simple for them to make a choice. This can be seen in the way Table 7 is formed by ranking the results from Table 6.

This model can be further extended by incorporating the importance factor, allowing it to be employed in more complex scenarios when many disasters are occurring at the same time. When it comes to the ERN, some bridges in the network might be more important than others. And furthermore, the model might be expanded to incorporate even more elements while still maintaining the key aspects. This could help solve ERN problems from a fresh perspective.

Table 9: Cumulative occurrence probabilities method based on the number of usable bridges.

State number	Occurrence probability	Cumulative occurrence probability	Maximum number of usable bridges
1	0.0144	0.0144	
2	0.0336	0.048	
3	0.0216	0.0696	1
4	0.0144	0.084	
5	0.0096	0.0936	
6	0.0216	0.1152	
7	0.0504	0.1656	
8	0.0336	0.1992	
9	0.0224	0.2216	
10	0.0504	0.272	
11	0.0216	0.2936	2
12	0.0144	0.308	
13	0.0324	0.3404	
14	0.0096	0.35	
15	0.0216	0.3716	
16	0.0144	0.386	
17	0.0504	0.4364	
18	0.0336	0.47	
19	0.0756	0.5456	
20	0.0224	0.568	
21	0.0504	0.6184	3
22	0.0336	0.652	
23	0.0144	0.6664	
24	0.0324	0.6988	
25	0.0216	0.7204	
26	0.0144	0.7348	
27	0.0336	0.7684	
28	0.0756	0.844	
29	0.0504	0.8944	4
30	0.0336	0.928	
31	0.0216	0.9496	
32	0.0504	1	5

4.3. The Network States Sampling. This section does not belong to either the methodology or the results sections. For larger problems, the following approaches would be a powerful aid to the proposed paradigm. We may not be able to consider all states and solve the model in larger networks. As a result, a sampling approach would be desired.

To sample the states of a larger network with more bridges (from an $M \subset S$ complex), the cumulative failure sampling method has been introduced in two ways: the number of usable bridges and the probability of occurrence. This method is proposed based on the approach presented in Edrissi et al. [32].

4.3.1. Cumulative Failure Method Based on the Number of Usable Bridges. In the cumulative failure method, samples from different network states with a maximum number of usable bridges are selected. The state number, occurrence probability, cumulative occurrence probability, and the maximum number of usable bridges are presented in Table 9. In this table, the cumulative occurrence probability is the sum of the samples' occurrence probabilities. Considering the presence of 5 bridges and possible failure states in the present case study, the sample types include 5 categories. Each category is settled based on the number of usable bridges. For example, if we choose states with the maximum number of 1 usable bridge, we will find a category consisting of 6 members (see Table 9). Furthermore, states with the maximum number of 5 usable bridges include all the 32 possible states.

4.3.2. Cumulative Failure Method Based on Probability of Occurrence. In this method, different types of samples are categorized based on the occurrence probability nearby value. According to Table 10, the occurrence probability values are arranged from very high to very low, and 32 states are divided into five categories (very high, high, medium, low, and very low).

4.3.3. Sampling Methods. Using the proposed sampling method, the obtained results based on the number of samples, the percentage of the sample, the cumulative probability of occurrence, and the percentage of error are presented in Table 11. The percentage of error indicates the absolute value of the objective function's distance from the optimal value by considering all states (based on the selected model).

As it was mentioned earlier, the cumulative failure sampling approach has been introduced in two methods to sample the states of a larger network with more bridges

Table 10: Cumulative occurrence probabilities method based on the occurrence probability category.

State number	Occurrence probability	Cumulative occurrence probability	Occurrence probability category
19	0.0756	0.0756	Very high
28	0.0756	0.1512	
7	0.0504	0.2016	High
10	0.0504	0.2520	
17	0.0504	0.3024	
21	0.0504	0.3528	
29	0.0504	0.4032	
32	0.0504	0.4536	
2	0.0336	0.4872	Medium
8	0.0336	0.5208	
18	0.0336	0.5544	
22	0.0336	0.5880	
27	0.0336	0.6216	
30	0.0336	0.6552	
13	0.0324	0.6876	
24	0.0324	0.7200	
9	0.0224	0.7424	Low
20	0.0224	0.7648	
3	0.0216	0.7864	
6	0.0216	0.8080	
11	0.0216	0.8296	
15	0.0216	0.8512	
25	0.0216	0.8728	
31	0.0216	0.8944	
1	0.0144	0.9088	Very low
4	0.0144	0.9232	
12	0.0144	0.9376	
16	0.0144	0.9520	
23	0.0144	0.9664	
26	0.0144	0.9808	
5	0.0096	0.9904	
14	0.0096	1.0000	

Table 11: Sampling method.

Type of cumulative failure method	Sampling approach	Number of samples	Sample's percentage	% cumulative occurrence probability	% error (distance from the total length optimal value)
The number of usable bridges	One usable and less	6	19	11.52	2.20
	Two usable and less	16	50	38.60	1.63
	Three usable and less	26	81	73.48	0.36
	Four usable and less	31	97	94.96	0.08
	Five usable and less	32	100	100.00	0.00
The probability of occurrence	"Very high" occurrence	2	6	15.12	0.60
	"High" to "very high" occurrence	8	25	45.36	0.60
	"Medium" to "very high" occurrence	16	50	72.00	0.60
	"Low" to "very high" occurrence	24	75	89.44	0.48
	"Very low" to "very high" occurrence (all)	32	100	100.00	0.00

(from an $M \subset S$ complex): the number of usable bridges and the probability of occurrence.

In the sampling failure method based on the number of usable bridges and the results of Table 9, five approaches (one usable and less, two usable and less, three usable and less, four usable and less, and five usable and less) have been introduced and mentioned in Table 11. In this method, the maximum possible error, taking into account only six samples of the possible states (one usable bridge and less), has been about 2.20%, and the cumulative occurrence probability was 11.52%. By increasing the number of samples to 26 (three usable bridges and less), the cumulative

occurrence probability was 73.48%, and the possible error dropped to 0.36%.

In sampling by cumulative failure method based on probability of occurrence and using the results of Table 10, probability of occurrence approaches has been "very high," "high to very high," "medium to very high," "low to very high," and "very low to very high" (see Table 11). The sampling approach of the states with a very high probability of occurrence (including 2 samples, as indicated in Table 10) yielded a maximum error of 0.6 percent in this method (Table 11). However, by selecting 24 samples, the percentage of error has been reduced to 0.48%.

Thus, the higher the cumulative occurrence probability, the lower the error, and the number of samples can be considered as the criteria for the sampling method. The results show that the TNL (objective function) can be estimated before the disaster relief network's complete design, even with two samples and a minor error. The use of the cumulative failure method is recommended to solve problems in larger dimensions considering the conditions of the case study.

5. Conclusions

In this paper, we developed a method to determine the retrofitting bridge options in an emergency road network by using an optimization model and analytical methods. The TNL has been considered to compare the retrofitting options and improve the relief after a disaster. This methodology has also given the possibility of evaluating budget allocation options. We have designed the ERN for each possible failure condition regarding the total available budget.

The results show that the retrofitting of a single bridge may decrease the average length of the relief network significantly, and with minimum spending, the proposed network failure becomes less likely. The sample problem shows that even with a 33% reduction in the retrofitting budget, we might achieve a more robust emergency relief network after a disaster. Furthermore, it is mentioned how we can resolve the bridge reinforcement problem by solving the emergency network design problems simultaneously. Finally, not only can we reduce the risks of the network operation, but we can also achieve the emergency roads retrofitting with adequate coverage and desired reliability, using a smaller network length and less budget.

5.1. Limitation and Future Studies. Despite the total damage or blockage of a part of the bridge, the bridge will be either usable or unusable. So, in this study, each bridge's state after the disaster is remarked in two forms of functional or nonfunctional, respectively, denoted with 1 or 0. These states can be set to continuous variables in future studies.

The earthquake scenario related to data presented in Table 2 was used to test our model. However, we may apply our model to other earthquake scenarios that are analogous to Table 2 in most ways. The proposed model could even be developed and utilized in future studies for scenarios that include earthquakes and other disasters at the same time.

For the purposes of our research, we assumed that "I" (importance factor) equalled 1 for all trips. Since all trips have the same value for "I," our model will have no flaws, and in other situations, our methodology can always identify between the various kinds of trips. Different values for "I" may be considered in comprehensive researches, which would be influenced by the policymakers' priorities and attitudes.

According to the proposed five-stage methodology and the proposed sampling method, it is possible to implement the model (at an acceptable time) for real transportation networks. Also, different disaster scenarios can be considered in the proposed model.

Data Availability

The data used to support the findings of this study are included in the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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