Natural Hazards (2020) 100:69–88
https://doi.org/10.1007/s11069-019-03799-7

ORIGINAL PAPER

Analysis of the susceptibility of interdependent infrastructures using fuzzy input–output inoperability model: the case of flood hazards in Tehran

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Received: 6 February 2018 / Accepted: 18 September 2019 / Published online: 26 September 2019

Abstract

Advancement in technology has contributed to increment in complexity of systems and infrastructures. Furthermore, it has complicated the management of systems to deal with natural hazards. Input–output inoperability model (IIM) is a simple method to characterize the impacts of natural hazards on interconnected infrastructures. In this paper, the impacts of a flood hazard on six critical infrastructures in Tehran metropolitan have been assessed by using IIM. The computational results show that energy and transportation infrastructures are the most influencing infrastructures, while emergency services and healthcare infrastructures are the most influenced infrastructures. All data required to evaluate this case study have been collected using questionnaires and converted to fuzzy interdependency values. To increase decision-making power, the developed fuzzy matrix has been arranged for different risk levels (from absolutely optimistic to absolutely pessimistic) and confidence levels (from absolutely confident to absolutely non-confident). Afterward, the interdependency matrix has been deffuzified, and inoperability of infrastructures has been calculated by the IIM for seven different initial conditions. Finally, a sensitivity analysis has been conducted to incorporate the risk levels and confidence levels to determine values of inoperability under the above-mentioned conditions. The ranking for both of the influencing and the influenced infrastructures has also been provided. This ranking helps decision makers to manage natural hazard risks effectively by appropriate resource allocation. It also helps to realize the interdependencies among infrastructures and to determine the inoperability of infrastructures before natural hazards. This would help decision makers to mitigate the risk and prepare the society well in advance.

Keywords Input–output inoperability model · Complex system · Risk analysis · Natural hazard · Critical infrastructure · Fuzzy number

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1 Introduction

One of the most considerable factors in the economic growth of under-developing countries is about the development of their infrastructures. To gain favorable economic growth, establishment and maintenance of such infrastructures are essential for providing satisfactory services. Critical infrastructures are usually the ones that inoperability of them would disrupt commerce, economy, national security, providing public services, and so forth. Furthermore, advancement in information technology expanded interdependencies among infrastructures. To diminish the vulnerability of infrastructures, analyzing and evaluating large-scale systems become more important (Haimes and Jiang 2001). War, terrorist operation, or natural hazard would negatively affect infrastructures and cause significant losses. Due to internal relation and interdependencies among infrastructures, inoperability of one infrastructure would also affect other infrastructures (called ripple effect) (Jiang and Haimes 2004).

The previous studies proposed different mathematical approaches to investigate such infrastructures with interdependencies. All these approaches aim to recognize, evaluate, and minimize the risk of domino effects caused by infrastructures' inoperability (Oliva et al. 2011). The IIM is a simple approach for the assessment of large-scale and complex systems (Setola et al. 2009). The IIM studies how an occurrence would affect a complicated system consisting of multiple subsystems with interdependencies. This type of formulation is capable of analyzing and demonstrating the status of a system in the static and dynamic conditions. Determining the technical coefficient matrix is one of the main steps in the implementation of this model. The technical coefficient matrix stores all specifications of the system. To specify this matrix, input–output tables are applied if they are available. Otherwise, this matrix is determined using the opinion of experts and questionnaires (Setola and De Porcellinis 2008), but it might decrease the confidence level of results. To resolve this problem, conducting a sensitivity analysis regarding the confidence level of solutions could help decision makers.

In this paper, the technical coefficients matrix is the first step determined using the opinion of experts and questionnaires. Afterward, each of these matrices will be assessed by the IIM in the static condition and will be compared to each other. The main intention of this study is to determine how different risk and confidence levels would affect the final condition of systems.

The rest of this paper is organized as follows: a review of the literature is provided in Sect. 2. In Sects. 3 and 4, the fuzzy IIM (FIIM) is proposed, and a real case study of the flood in Tehran is evaluated, respectively. Eventually, a conclusion is provided in Sect. 5.

2 Literature review

Haimes and Jiang (2001) proposed the primary IIM based on the economic model of Leontief and solved some instances to explain how it works in both static and dynamic conditions. Jiang and Haimes (2004) stated that inoperability of infrastructures with interdependencies might cause significant losses. This paper only focused on economic losses. Finally, they combined the IIM and OR modeling methods and proposed four optimization models for this problem. Haimes et al. (2005) investigated how to determine the technical coefficients using the data stored in BEA.[1] Moreover, they applied it to the risk management problems using the IIM and multi-regional IIM (MRIIM). Then, they introduced the applications, similarities, and differences between these two formulations in both static and dynamic conditions. Santos (2006) also studied the IIM in both static and dynamic conditions and compared how determining the technical coefficients in these conditions differs from each other. Fenton and Wang (2006) addressed a multi-criteria decision-making (MCDM) problem and studied different risk levels (from absolutely optimistic to absolutely pessimistic) and confidence levels (from absolutely confidence to absolutely non-confident). Since infrastructures are becoming more interdependent, Setola (2007) evaluated the interdependencies among 57 economic units in Italy. The results obtained in this paper also showed that such interdependencies are increased among these units, which makes the management of them more complicated.

Setola and De Porcellinis (2008) assessed the effectiveness of the MII for calculation of risks in systems with interdependencies. They also proposed a new approach to determine the fuzzy technical coefficients matrix using questionnaires. Finally, they implemented this approach for infrastructures in Italy. They indicated that elements of the IIM are extracted according to economic data. Taking into account that there would be another type of influential data, which would also be effective, there is the possibility of mistake. Therefore, they used questionnaires and established fuzzy interdependency matrix. Oliva et al. (2011) studied systems in which sufficient data are not available. They used fuzzy questionnaires at different time intervals and opinion of experts to gather required data. They proposed a model, named fuzzy dynamic IIM, where all elements in interdependency matrix and inoperability value of the system are defined based on the fuzzy notion. Guo (2013) prepared a report of BEA organization and explained how raw data are converted to the technical coefficients. Aviso et al. (2016) implemented the IIM to study the interdependencies created among organizations by their workforce. The main intention of this paper is to minimize the possible disruptions in serving external customers.

3 A hybrid approach of fuzzy input–output inoperability models

Note that all data required to evaluate this case study have been acquired using questionnaires and then converted to form fuzzy interdependency matrix. To increase the decision-making power, this matrix has been calculated for different risk levels (from absolutely optimistic to absolutely pessimistic) and confidence levels (from absolutely confident to absolutely non-confident). Afterward, the technical coefficients have been deffuzified and evaluated by the IIM. Further details have been provided in the following sections.

3.1 Fuzzy input–output inoperability models

In this paper, we have proposed an IIM to evaluate a system consisting of some infrastructures with interdependencies. Inputs and outputs in this model are the inoperability probability of infrastructures. The performance of each infrastructure is determined using a real number between 0 and 1, where 0 refers to a case that the infrastructure is completely safe and 1 refers to the complete inoperability of the infrastructure. In first, we consider that all infrastructures

[1] www.bea.gov.

are completely safe, and the inoperability probability of them is equal to 0. However, the occurrence of natural hazards might deteriorate the infrastructures, and its inoperability probability modifies to a value larger than 0. Since infrastructures are interdependent, it could intensify the inoperability of them and result in their partial or complete destruction.

In these circumstances, we need to determine the interdependencies and initial damage imposed to infrastructures to estimate the final status of the system. We define a stable condition where the system is consistent, and inoperability of infrastructures does not increase. The stable condition could happen by the partial or complete inoperability of infrastructures (Haimes and Jiang 2001). Equation (1) shows the general equation of the IIM proposed by Leontief.

$$X = AX + C \tag{1}$$

where C refers to the initial damage imposed to infrastructures, A refers to the square matrix of interdependencies, and X refers to the inoperability of infrastructures in stable condition. Note that the elements of the main diagonal in A are equal to 0, and other elements are real numbers between 0 and 1. A is a positive stable matrix, which shows the direct impact of two infrastructures on each other. The simplified form of Eq. (1) is written as follows:

$$X = (I - A)^{-1}C = SC \tag{2}$$

where S refers to the steady-state matrix, and shows all the first-, second- and third-degree effects of infrastructures on each other. To reach the steady-state condition, the following equation should be true:

$$S = [I - A]^{-1} = I + A + A^2 + A^3 + \dots \tag{3}$$

Determining A is important since it contains all essential data of the system. In this paper, we have implemented the method proposed by Setola and De Porcellinis (2008) to determine this matrix. When there are no sufficient precise data to define the interdependencies among infrastructures, this method uses questionnaires and opinion of experts to gather the required data. These questionnaires have been extracted from Setola et al. (2009), and other scholars have also applied the same approach for determining matrix A (e.g., Setola and Theocharidou 2016; Klein and Klein 2019; Yu et al. 2015; Asimopolos et al. 2018). We can estimate a_{ij} parameters with the help of experts. They need to evaluate the impact of flood on the infrastructure caused by the complete absence of the services provided by any other infrastructure. For this purpose, sector-specific questionnaires were submitted and each expert was invited to quantify the impact using the linguistic expressions reported in Table 1. Moreover, each expert had to qualify their confidence about their evaluations using the quantifiers described in Table 2. In order to aggregate the collected data, a measurement of the reliability of each expert has been adopted using Table 3, ranking them on the base of their experience and position. In addition, the reliability of expert responses was also assessed using the Cronbach's alpha index. It is noteworthy that all these tables are defined based on linguistic variables.

Afterward, we have used normalized triangular fuzzy numbers to convert these questionnaires as follows:

$$a_{ij} = [l \; m \; u \; h] \tag{4}$$

where m refers to the main value obtained based on Table 1. l and u refer to the lower and upper estimation for m, respectively; these two values are calculated using m and Table 2.

Table 1 Estimation for the effects of natural hazards on infrastructures (Setola et al. 2009)

Impact	Description	Value
Nothing	The occurrence does not induce any effect on the infrastructure	0
Negligible	The occurrence induces negligible and geographically bounded consequences on services that has no direct impact on the infrastructure's operability	0.0125
Very limited	The occurrence induces very limited and geographically bounded consequences on services that has no direct impact on the infrastructure's operability	0.02
Limited	The occurrence induces consequences only on services that has no direct impact on the infrastructure's operability	0.025
Some degradations	The occurrence induces very limited and geographically bounded consequences on the capability of the infrastructure to provide its services	0.05
Circumscribed degradation	The occurrence induces visible geographically bounded consequences on the capability of the infrastructure to provide its services	0.075
Significant degradation	The occurrence significantly degrades the capability of the infrastructure to provide its services	0.125
Provide only some services	The occurrence impact is such that the infrastructure is able to provide only some residual services	0.2
Quite complete stop	The infrastructure is almost entirely inoperable	0.3
Stop	The infrastructure is entirely inoperable	0.5

Eventually, h refers to the largest membership degree, which is calculated based on Table 3. Using Eq. (3), fuzzy elements of the technical coefficients are determined as follows:

$$\tilde{a}_{ij} = \begin{cases} l = \frac{\sum_k a_{ij}^k.l \times a_{ij}^k.h}{\sum_k a_{ij}^k.h} \\ 0 \\ m = \frac{\sum_k a_{ij}^k.m \times a_{ij}^k.h}{\sum_k a_{ij}^k.h} \\ 0 \\ u = \frac{\sum_k a_{ij}^k.u \times a_{ij}^k.h}{\sum_k a_{ij}^k.h} \\ 0 \\ h = \max\left\{ a_{ij}^k.h \right\} \end{cases} \quad \forall i,j \tag{5}$$

Then, we determine the influencing and influenced infrastructures based on Eqs. (6) and (7), respectively, as follows:

$$\tilde{\delta}_i = \sum_{j=1}^{n} a_{ij} \tag{6}$$

$$\tilde{\theta}_j = \sum_{i=1}^{n} a_{ij} \tag{7}$$

Table 2 Confidence of experts with respect to their opinions (Setola et al. 2009)

Confidence	Description	Value
+	Good confidence	0
++	Relative confidence	0.0125 ±
+++	Limited confidence	0.025 ±
++++	Almost uncertain	0.0375 ±
+++++	Completely uncertain	0.05 ±

Table 3 Experience of experts (Setola et al. 2009)

Class	Description	Value
A	Expert with large operative experience and with good knowledge of the whole infrastructure	1
B	Expert with operative experience and with some knowledge of the whole infrastructure	0.9
C	Expert with large operative experience but with a specific/bounded point of view	0.8
D	Expert with operative experience but with a specific/bounded point of view	0.7
E	Expert with large (theoretical) knowledge of the whole infrastructure (e.g., academics and consultants)	0.6
F	Expert with large (theoretical) knowledge of some relevant elements of the infrastructure (e.g., academics)	0.5

Since natural hazards are scarce and there are no sufficient data concerning them, data are gathered using questionnaires; therefore, there is a probability of mistake. Based on this reasoning, we have designed a comprehensive sensitivity analysis in the following subsection in order to study the fuzzy elements of the technical coefficients regarding risk and confidence levels (Fenton and Wang 2006).

3.2 Sensitivity analysis

3.2.1 Sensitivity analysis based on risk levels

Each element of the fuzzy interdependency matrix is considered neutral. Furthermore, four levels of optimism, such as absolutely optimistic, optimistic, pessimistic, and absolutely pessimistic, are studied for the sensitivity analysis based on risk levels. If each element in the technical coefficients is defined as $\tilde{a}_{ij} = \left[a_1, a_2, a_3\right]$, then we convert them using Table 4. To define optimism and pessimism of experts, we have to keep in mind first that the result of the calculation is cost related. So the matrix A with larger elements produces more cost. We know that the elements of matrix A are triangular fuzzy numbers. The optimism or pessimism of the expert affects the location of the middle number, which is the vertex of the fuzzy number triangle. According to Table 4, the optimism expert moves the middle number to the left to reduce the fuzzy number and reduce costs. And the pessimism expert moves the middle number to the right to enlarge the fuzzy number and to increase costs. Note that we originated Table 4 from Fenton and Wang (2006).

Given that we have to determine the inoperability risk of infrastructures in this study, we will just use the column of negative criteria (cost) provided in Table 4.

Table 4 Linguistic variables for different levels of optimism (Fenton and Wang 2006)

Linguistic variables	The triangular fuzzy number for benefit criteria $[a_1, a_2, a_3]$	The triangular fuzzy number for cost criteria $[a_1, a_2, a_3]$
Absolutely Optimistic (AO)	$[a_1, a_3, a_3]$	$[a_1, a_1, a_3]$
Optimistic (O)	$[a_1, (a_2 + a_3)/2, a_3]$	$[a_1, (a_2 + a_1)/2, a_3]$
Neutral (N)	$[a_1, a_2, a_3]$	$[a_1, a_2, a_3]$
Pessimistic (P)	$[a_1, (a_2 + a_1)/2, a_3]$	$[a_1, (a_2 + a_3)/2, a_3]$
Absolutely pessimistic (AP)	$[a_1, a_1, a_3]$	$[a_1, a_3, a_3]$

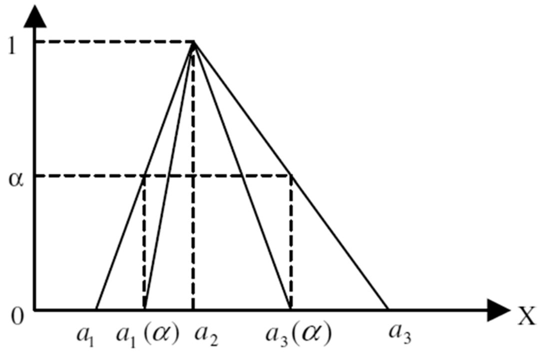


Fig. 1 A typical triangular fuzzy number and its corresponding α-cuts

3.2.2 Sensitivity analysis based on confidence levels

In the sensitivity analysis designed based on risk levels, we have considered the optimism and pessimism of experts that the optimism and pessimism indicate lower bound and upper bound of triangular fuzzy numbers, respectively. Then, we have considered how much experts are confident on their opinion using the α-cut. As shown in Fig. 1, we use the notion of the α-cut method to study the confidence level of the decision makers on the opinion of experts. In this method, $\alpha \in [0, 1]$ determines the confidence level of decision makers about a specific fuzzy number (i.e., the opinion of an expert). Using this method, we will calculate another fuzzy number, incorporating the confidence level of the decision makers. Note that larger value of α denotes the higher level of confidence.

To consider the α level of confidence in $\tilde{a} = [a_1, a_2, a_3]$, we use Eq. (8):

$$\tilde{a}^{\alpha} = [a_1(\alpha), a_2, a_3(\alpha)] = (a_1 + \alpha(a_2 - a_1), a_2, a_3 - \alpha(a_3 - a_2)) \quad (8)$$

To conduct a sensitivity analysis based on confidence levels, we should consider $\boldsymbol{l}$ levels of confidence. For this purpose, we apply Eq. (9) to calculate the values of α (Setola 2007).

$$\alpha = (k - 1)/(l - 1) \quad \forall k = 1, \ldots, l \text{ (where } l \geq 2) \quad (9)$$

In this paper, we have assumed five levels of confidence, which are provided in Table 5 (Setola 2007).

The neutral level is referring to the initial fuzzy number originated from questionnaires.

Table 5 α-Cut levels for confidence levels

Confidence level	$\%\alpha$
Absolutely non-confident (ANC)	0
Non-confident (NC)	25
Neutral (N)	50
Confident (C)	75
Absolutely confident (AC)	100

3.3 Defuzzification

After the sensitivity analysis mentioned before, we aim to defuzzify the fuzzy elements of the technical coefficients using the vertex method. The basis of this method is according to the distance from the positive ideal and negative ideal points.

If we consider $\tilde{a} = \left[a_1, a_2, a_3\right]$ and $\tilde{b} = \left[b_1, b_2, b_3\right]$ as two fuzzy numbers, the distance between them is calculated based on the vertex method as follows:

$$d\left(\tilde{a}, \tilde{b}\right) = \left\{\left[\left(a_1 - b_1\right)^2 + \left(a_2 - b_2\right)^2 + \left(a_3 - b_3\right)^2\right]/3\right\}^{\left(\frac{1}{2}\right)} \tag{10}$$

Since the ideal and negative points for the normalized interdependency matrix are equal to $p^+ = [1, 1, 1]$ and $p^- = [0, 0, 0]$, respectively, we have deffuzified the fuzzy number based on Eq. (10).

$$p = \left(d^- + 1 - d^+\right)/2 \tag{11}$$

We use Eq. (1) and the numbers obtained by Eqs. (10) and (11) to estimate the final status of the system. It should be mentioned that the type and severity of the event are not effective in calculating the dependency matrix (A), because the extent of infrastructures dependency to each other remains constant under any circumstances and in the occurrence of any flood. Then, according to the occurrence of different floods which lead to any given initial perturbation called the matrix (C), we calculate the extent to which these infrastructures become inoperable.

4 Case study

Tehran city, the capital of Iran, is the largest and most important accumulation of facilities, fund, and work force. Flood is one of the most important natural hazards threatening Tehran. Based on the report provided by the Ministry of Energy in 2015, Tehran is the fifth most affected city in Iran by the consequences of floods. This report indicates that 28 floods occurred from 1955 to 2014 in this city, and as a consequence, 2550 people have been killed and they caused \$1.87 billion US dollar economic losses. To investigate the importance of flood severity in Tehran, two major floods have been used as case studies in this paper. The most destructive flood of Tehran occurred in Tajrish in 1987. This flood killed about 300 people, caused \$304 million US dollar economic losses, and destroyed more than 120 houses. Furthermore, we can refer to the other flood occurred in Ken in 2015. This flood also killed 16 people and caused significant losses on public facilities, and water and electricity infrastructures Ahadnejad et al. (2016). Although the amount of rainfall has dropped in recent years, unforeseen changes of weather condition may lead to floods. Thus, it is evident that floods could impose considerable economic losses to the infrastructures and menace the life of many people. For this reason, we have studied and analyzed effects of floods on the interdependency of infrastructures of Tehran in this study.

In this study, a system consisting of six critical infrastructures of Tehran (the capital of Iran) has been investigated. Since urban infrastructure interdependencies are inevitable, it is necessary to evaluate the cascading events and the interactions of the critical infrastructure in emergency situations (e.g., after a natural hazard event). Due to the unique nature of each individual disaster, selected infrastructures are critical for early post-disaster times (first 1–10 h). Therefore, a number of unanticipated infrastructures are given next priorities, and the purpose of this article is to address the initial disaster situation. For example, the banking and retail sectors have less priority in the early stages of a disaster, but transport infrastructure sector that they need to be functional for transporting the critical goods to affected population or evacuating the injuries to healthcare facilities, are considered top priority. Lack of information through communication or power outages can significantly increase the severity of the disaster, or lack of access to clean water for personal hygiene can have adverse consequences such as disease outbreaks. In addition, hospital and emergency services play a vital role in rescuing the injured affected communities. Therefore, as stated earlier, some infrastructures in the early hours of the disaster occurrence are more important than the rest of the infrastructures which had motivated us to conduct this research to focus on critical infrastructures. These infrastructures include communication, emergency services, energy, healthcare, transportation systems, and water and wastewater systems sectors. Figure 2 illustrates a typical schema of this system.

We have selected 25 experts from the crisis management organization of Tehran and asked them to complete the questionnaire. Most of these experts have about 5 to 10 years of experiences because this organization has been recently established. The respondents' profile is provided in Table 6.

Then, we have determined the technical coefficients as follows:

$$A = \begin{bmatrix} 0 & [0.019,0.026,0.033] & [0.140,0.146,0.152] & [0.004,0.007,0.009] & [0.035,0.039,0.042] & [0.003,0.006,0.008] \\ [0.104,0.11,0.115] & 0 & [0.147,0.151,0.155] & [0.059,0.064,0.069] & [0.195,0.202,0.210] & [0.051,0.056,0.061] \\ [0.035,0.042,0.048] & [0.024,0.039,0.053] & 0 & [0.003,0.007,0.011] & [0.020,0.024,0.027] & [0.024,0.028,0.033] \\ [0.049,0.054,0.058] & [0.046,0.051,0.056] & [0.073,0.078,0.083] & 0 & [0.115,0.120,0.125] & [0.051,0.056,0.062] \\ [0.040,0.046,0.051] & [0.042,0.049,0.056] & [0.058,0.063,0.068] & [0.003,0.006,0.009] & 0 & [0.008,0.013,0.018] \\ [0.024,0.030,0.037] & [0.034,0.039,0.044] & [0.067,0.071,0.076] & [0.003,0.005,0.008] & [0.009,0.012,0.016] & 0 \end{bmatrix}$$

The reliability of expert responses was also assessed using the Cronbach's alpha index, as shown in Table 7.

In the next step, we have converted the technical coefficients based on five risk levels introduced in Table 4. For instance, the following matrix shows the technical coefficients for the optimistic risk level.

$$A_O = \begin{bmatrix} 0 & [0.019,0.023,0.033] & [0.140,0.143,0.152] & [0.004,0.005,0.009] & [0.035,0.037,0.042] & [0.003,0.004,0.008] \\ [0.104,0.107,0.115] & 0 & [0.147,0.149,0.155] & [0.059,0.061,0.069] & [0.195,0.199,0.210] & [0.051,0.054,0.061] \\ [0.035,0.038,0.048] & [0.024,0.032,0.053] & 0 & [0.003,0.005,0.011] & [0.020,0.022,0.027] & [0.024,0.026,0.033] \\ [0.049,0.052,0.058] & [0.046,0.049,0.056] & [0.073,0.076,0.083] & 0 & [0.115,0.117,0.125] & [0.051,0.053,0.062] \\ [0.040,0.043,0.051] & [0.042,0.045,0.056] & [0.058,0.061,0.068] & [0.003,0.004,0.009] & 0 & [0.008,0.010,0.018] \\ [0.024,0.027,0.037] & [0.034,0.037,0.044] & [0.067,0.069,0.076] & [0.003,0.004,0.008] & [0.009,0.011,0.016] & 0 \end{bmatrix}$$

Afterward, each of these five matrices is converted to five other matrices to cover all five confidence levels (25 matrices are finally created). For example, the following matrix

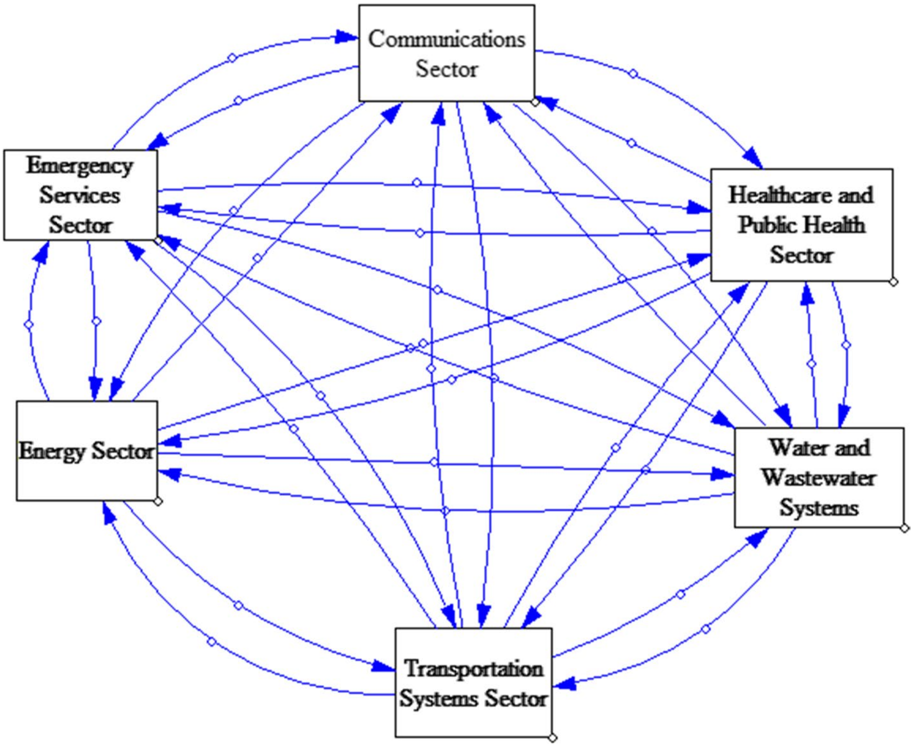


Fig. 2 Schematic view of the system

Table 6 Information of experts who have completed questionnaires

Education	
Bachelor degree	Master degree
54%	46%

Table 7 The reliability of expert using the Cronbach's alpha index

	Infrastructure	Cronbach's alpha
1	Communications	0.747
2	Emergency services	0.752
3	Energy	0.882
4	Health care	0.894
5	Public transportations	0.740
6	Wastewater system	0.776
7	Total	0.892

Table 8 Ranking of infrastructures regarding the influencing index

Rank	Infrastructure	Influencing criterion ($\tilde{\theta}_j$)
1	Energy sector	0.7083
2	Transportation sector	0.5757
3	Communication sector	0.5195
4	Emergency services sector	0.4102
5	Water and water waste sector	0.2694
6	Healthcare sector	0.162

demonstrates the technical coefficients of the initial matrix (i.e., A) for the optimistic risk level and non-confident confidence level.

$$A_{O/NC} = \begin{bmatrix} 0 & [0.020,0.023,0.030] & [0.141,0.143,0.150] & [0.005,0.005,0.008] & [0.035,0.037,0.041] & [0.003,0.004,0.007] \\ [0.105,0.107,0.113] & 0 & [0.147,0.149,0.153] & [0.059,0.061,0.067] & [0.196,0.199,0.207] & [0.052,0.054,0.059] \\ [0.036,0.038,0.046] & [0.026,0.032,0.047] & 0 & [0.004,0.005,0.010] & [0.021,0.022,0.026] & [0.024,0.026,0.031] \\ [0.050,0.052,0.057] & [0.047,0.049,0.054 & [0.074,0.076,0.081] & 0 & [0.115,0.117,0.123] & [0.051,0.053,0.060] \\ [0.041,0.043,0.049] & [0.043,0.045,0.053] & [0.059,0.061,0.067] & [0.003,0.004,0.008] & 0 & [0.008,0.010,0.016] \\ [0.024,0.027,0.034] & [0.035,0.037,0.042] & [0.067,0.069,0.074] & [0.003,0.004,0.007] & [0.009,0.011,0.015] & 0 \end{bmatrix}$$

Using Eqs. (8) and (9), we have determined the deterministic matrices of all interdependency matrices calculated in the previous steps.

$$A_{\mathrm{O/NC}} = \begin{bmatrix} 0 & 0.025 & 0.145 & 0.0060 & 0.038 & 0.005 \\ 0.108 & 0 & 0.150 & 0.062 & 0.201 & 0.055 \\ 0.040 & 0.036 & 0 & 0.006 & 0.023 & 0.027 \\ 0.053 & 0.050 & 0.077 & 0 & 0.119 & 0.055 \\ 0.044 & 0.047 & 0.062 & 0.005 & 0 & 0.012 \\ 0.029 & 0.038 & 0.070 & 0.005 & 0.012 & 0 \end{bmatrix}$$

As stated previously, the ranking of the most influencing and the most influenced infrastructures is calculated based on Eqs. (4) and (5). For instance, Tables 8 and 9 show the ranking of infrastructures for the initial interdependency matrix (i.e., A). These two rankings are valid for other interdependency matrices where their values slightly vary in comparison with each other.

Now, we have to evaluate the deterministic interdependency matrices using Eq. (1) to estimate the final status of the system. To do this, we have to know about the initial damage caused by the natural hazard to the infrastructures. Given that the floods mentioned in the article occurred years earlier and estimated infrastructure perturbation at that time is not accurately reported, it has been attempted to investigate the problem of lack of information for each of the infrastructures using sensitivity analysis. Therefore, the perturbation of each infrastructure is assumed to be between 0.1 and 0.7. So the effect of different levels of perturbation on the rate of infrastructure inoperability has been calculated. Also due to the lack of access to flood information at that time, we can randomly generate the perturbation rate of each of the infrastructures using the uniform distribution function, and analyzed their impact on the extent of infrastructure inoperability to determine the linear trend of inoperability of each infrastructure. We have defined 6 different cases. In the first case (C_1), all of the infrastructures lost half of their operability, and in the next 5 cases (C_2 to C_6), each infrastructure has become inoperable randomly as follows:

Table 9 Ranking of infrastructures regarding the influenced index

Rank	Infrastructure	Influenced criterion ($\tilde{\delta}_i$)
1	Emergency services sector	0.7700
2	Healthcare sector	0.5752
3	Communication sector	0.3556
4	Transportation sector	0.3474
5	Water and water waste sector	0.3096
6	Energy sector	0.2874

$$C_1 = \begin{bmatrix} 0.5 \\ 0.5 \\ 0.5 \\ 0.5 \\ 0.5 \\ 0.5 \end{bmatrix}, C_2 = \begin{bmatrix} 0.3 \\ 0.2 \\ 0.6 \\ 0.2 \\ 0.5 \\ 0.2 \end{bmatrix}, C_3 = \begin{bmatrix} 0.1 \\ 0.7 \\ 0.5 \\ 0.2 \\ 0.6 \\ 0.6 \end{bmatrix}, C_4 = \begin{bmatrix} 0.5 \\ 0.7 \\ 0.3 \\ 0.7 \\ 0.1 \\ 0.5 \end{bmatrix}, C_5 = \begin{bmatrix} 0.6 \\ 0.4 \\ 0.1 \\ 0.1 \\ 0.3 \\ 0.5 \end{bmatrix}, C_6 = \begin{bmatrix} 0.5 \\ 0.2 \\ 0.3 \\ 0.7 \\ 0.6 \\ 0.7 \end{bmatrix}$$

Finally, Table 10 shows the final status of the system under various risk and confidence levels. Note that we have considered the initial status of the system to be equal to C_1.

In Table 10, each section shows the final status of the system regarding risk and confidence levels. Table 10 shows that emergency services and healthcare sectors, which are the most influenced infrastructures, entirely become inoperable in all cases. This table shows that the final status of the system would be deteriorated when we move from absolutely optimistic (AO) toward absolutely pessimistic (AP) risk levels. In AP risk level, the final status of the system would become more consistent when we move from absolutely confident (AC) toward absolutely non-confident (ANC) confidence levels. This is rational since we will become ANC about the AP opinion of experts. In pessimistic (P) risk level, the final status of the system would also become more consistent when we move from AC toward ANC confidence levels.

In case of neutral (N) risk level, Table 10 shows that the final status of the system is not sensitive to the confidence level. In other words, the final status of the system does not change when we move from AC toward ANC confidence levels.

But in optimistic (O) and AO risk levels, moving from AC toward ANC confidence levels does not help the system as previous cases. To be more precise, Table 10 shows that the final status of the system would be deteriorated when we move from AC toward ANC confidence levels in O risk level. The AO risk level also does hold the same trend. In fact, the final status of the system would be deteriorated when we move from AC toward ANC confidence levels.

Tables 11 and 12 show the final status of the system with AO/AC and AP/AC risk and confidence levels under different initial damages, which show the most and least damage to the system, respectively. As shown in both of these tables, the most influenced infrastructure would become inoperable sooner than others. To be more precise, the emergency services and healthcare sectors would become inoperable for $C \geq 0.4$.

The results illustrated in Figs. 3 and 4 also show that there is around 26% difference between the results provided in these tables. In other words, the difference in opinion of

Table 10 The results obtained for the final status of the system

Confidence	Level of optimism				
	AO	O	N	P	AP
AC	0.724	0.758	0.797	0.840	0.889
	1	1	1	1	1
	0.675	0.712	0.752	0.798	0.849
	0.886	0.932	0.982	1	1
	0.720	0.759	0.801	0.848	0.902
	0.701	0.734	0.771	0.812	0.859
C	0.735	0.766	0.799	0.835	0.876
	1	1	1	1	1
	0.688	0.721	0.755	0.793	0.835
	0.901	0.944	0.987	1	1
	0.733	0.768	0.804	0.844	0.888
	0.712	0.773	0.807	0.845	0.886
N	0.748	0.772	0.798	0.826	0.858
	1	1	1	1	1
	0.701	0.726	0.753	0.783	0.815
	0.917	0.949	0.983	1	1
	0.747	0.773	0.802	0.833	0.867
	0.724	0.747	0.772	0.799	0.828
NC	0.761	0.779	0.799	0.820	0.843
	1	1	1	1	1
	0.715	0.734	0.754	0.777	0.800
	0.934	0.958	0.983	1	1
	0.761	0.781	0.803	0.826	0.851
	0.737	0.754	0.773	0.793	0.815
ANC	0.775	0.787	0.800	0.814	0.830
	1	1	1	1	1
	0.730	0.742	0.756	0.771	0.786
	0.952	0.968	0.985	1	1
	0.777	0.790	0.804	0.820	0.837
	0.750	0.761	0.774	0.787	0.802

experts would significantly affect the final status of the system. Furthermore, two of infrastructure would not be entirely inoperable with AO/AC risk and confidence levels where $C = 0.7$, while all infrastructures would be entirely inoperable with AP/AC risk and confidence levels where $C \geq 0.6$. In general, it can perceive that infrastructures arrive to the inoperability threshold later in AO/AC state compared to AP/AC state. Since the influenced amount in the emergency services and healthcare sectors is more than the four other sectors, in the different initial disruption levels, the inoperability amounts of them have difference significantly compared to the four other sectors. On the other hand, energy and the transportation sectors as the most influencing infrastructure play a key role in the whole system and should be planned and more precise to keep them in operability circumstances. Although Table 9 shows them in the lower rankings, their performance is less affected by other infrastructures and later become inoperable. This difference in the number and amount of inoperable infrastructures (between AO/AC and AP/AC risk and confidence

Table 11 The final status of the system with AO/AC risk and confidence levels under similar initial damages for each infrastructure

Infrastructure	C						
	0.1	0.2	0.3	0.4	0.5	0.6	0.7
Communication sector	0.145	0.290	0.434	0.579	0.724	0.869	1
Emergency services sector	0.202	0.405	0.607	0.810	1	1	1
Energy sector	0.135	0.270	0.405	0.540	0.675	0.810	0.945
Healthcare sector	0.177	0.355	0.532	0.709	0.886	1	1
Transportation sector	0.144	0.288	0.432	0.576	0.720	0.865	1
Water and water waste sector	0.140	0.280	0.421	0.561	0.701	0.841	0.981

Table 12 The final status of the system with AP/AC risk and confidence levels under same initial damages for each infrastructure

Infrastructure	C						
	0.1	0.2	0.3	0.4	0.5	0.6	0.7
Communication sector	0.178	0.356	0.534	0.712	0.889	1	1
Emergency services sector	0.252	0.503	0.755	1	1	1	1
Energy sector	0.170	0.339	0.509	0.679	0.849	1	1
Healthcare sector	0.220	0.440	0.661	0.881	1	1	1
Transportation sector	0.180	0.361	0.541	0.721	0.902	1	1
Water and water waste sector	0.172	0.344	0.515	0.687	0.859	1	1

levels) helps decision makers to analyze the disruptions; moreover, it might also help them to choose strategies in dealing with such occurrences. Determining the best and worst possible cases for hazards lets decision makers to deal with both cases. Therefore, conducting a sensitivity analysis regarding risk and confidence levels could provide better and more detailed results for decision makers. This also provides a wider range of estimations with respect to disruptions occurred and costs of implementing strategies to deal with them. Figures 3 and 4 show that infrastructures inoperability takes place later in optimistic case than pessimistic case. Inoperability level of emergency services and healthcare infrastructures differs from the other four infrastructures significantly since they are the most influencing infrastructures.

In addition, for the cases C_2 to C_6 when interdependencies correlation matrix A is AO/AC, final situation is calculated. Results are shown in Table 13.

Figures 5 and 6 illustrate the initial perturbation and the steady states of energy and public transportations infrastructures under different given initial perturbations.

As shown in Figs 5 and 6, when we randomly generate the perturbation rate of each of the infrastructures in the range [0.1–0.7], the values of inoperability of each of the sectors show a trend of being linear to be inoperable. It is evident that due to severity of interdependencies of matrix elements A and initial perturbations, trend of each of sector is different.

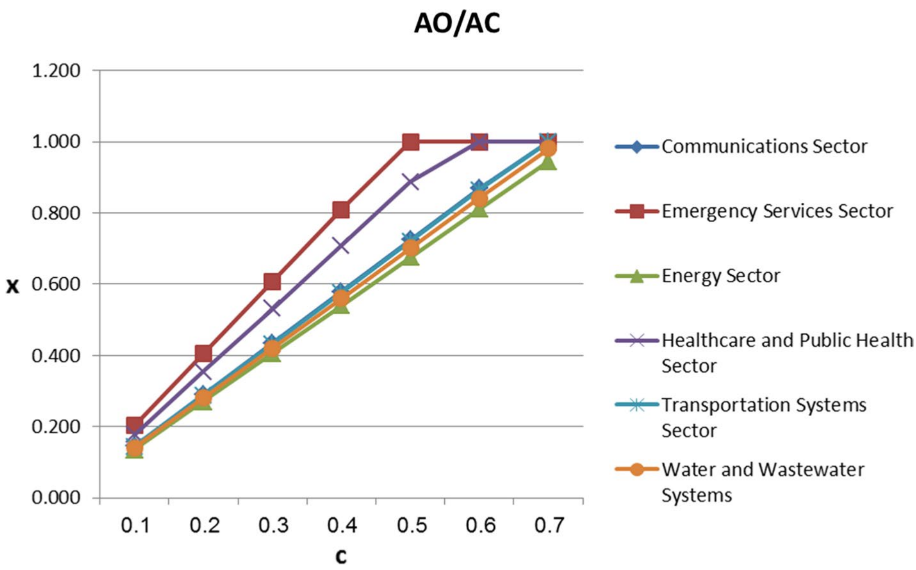


Fig. 3 The final status of the system with AO/AC risk and confidence levels under similar initial damages for each infrastructure

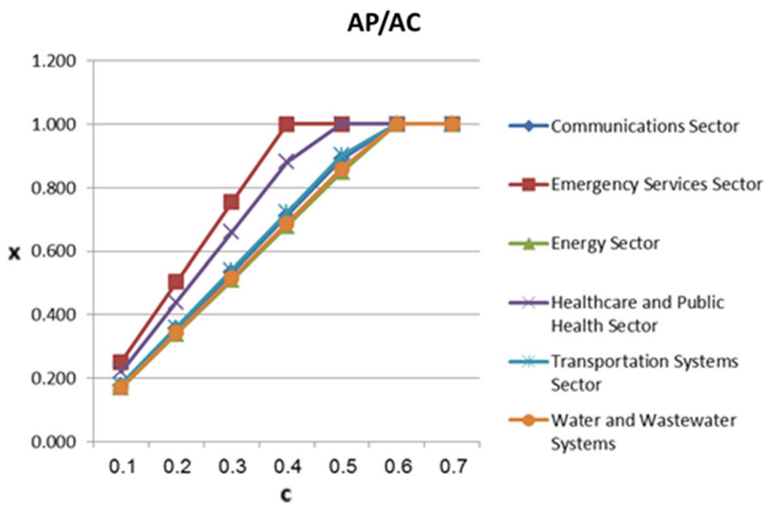


Fig. 4 The final status of the system with AP/AC risk and confidence levels under same initial damages for each infrastructure

The results obtained from sensitivity analysis based on experts' opinions and interdependencies correlation matrix *A* show system characteristics (which indicates system features) which have been divided into 25 different cases (such as optimistic–pessimistic responses, confidence levels). In Fig. 7, horizontal axis shows optimism (o) to pessimism (p) and vertical axis shows confidence levels. Based on sensitivity analysis of

Table 13 The final status of the system with AO/AC risk and confidence levels under randomly different initial damages for each infrastructure

	C_2	Steady state	C_3	Steady state	C_4	Steady state	C_5	Steady state	C_6	Steady state
Communications	0.30	0.5025	0.10	0.3297	0.50	0.6613	0.60	0.7139	0.50	0.6828
Emergency services	0.20	0.6195	0.70	1	0.70	1	0.40	0.7241	0.20	0.7067
Energy	0.60	0.7198	0.50	0.6572	0.30	0.4538	0.10	0.2396	0.30	0.4657
Health care	0.20	0.5049	0.20	0.5818	0.70	0.9955	0.10	0.3652	0.70	1
Public transportations	0.50	0.6676	0.60	0.7933	0.10	0.2988	0.30	0.4523	0.60	0.7791
Wastewater system	0.20	0.3603	0.60	0.7873	0.50	0.6725	0.50	0.6272	0.70	0.8586

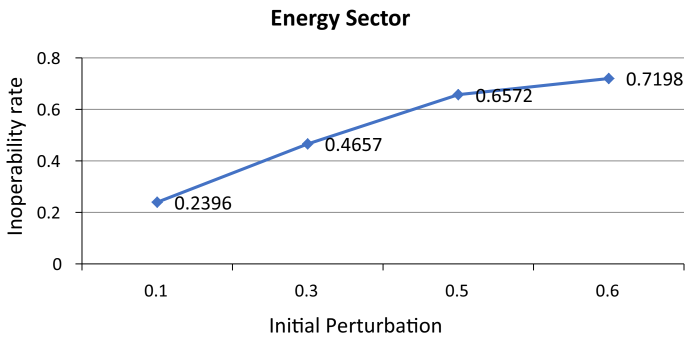


Fig. 5 The final status of the system with AO/AC risk and confidence levels under random different initial damages for energy infrastructure

Fig. 6 The final status of the system with AO/AC risk and confidence levels under random different initial damages for public transportation infrastructure

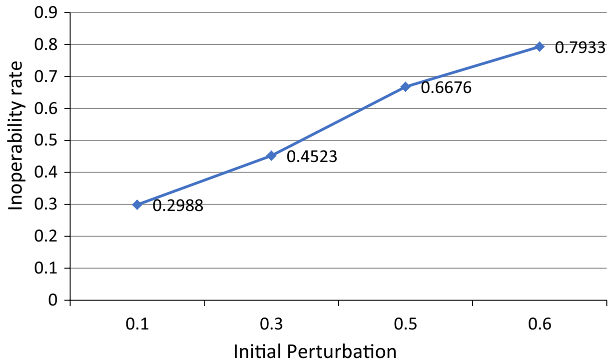
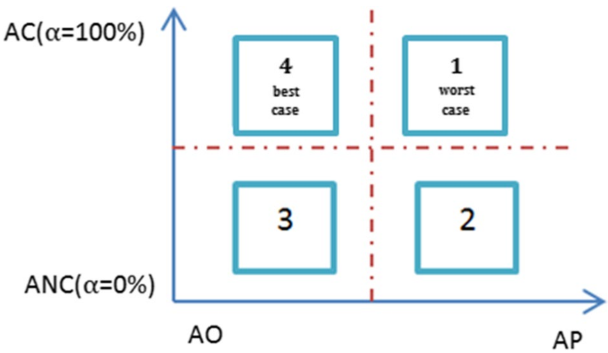


Fig. 7 Sensitivity analysis on matrix *A*



interdependencies matrix *A*, we realize that the opinions of absolutely pessimistic experts and absolutely confidence (AP/AC) generate interdependencies correlation matrices, which shows the worst situation for the system (most infrastructure inoperability). Reducing in experts' confidence leads to changes in matrix *A*, in which that final situation of perturbation in infrastructures show less. Following, absolutely optimistic and absolutely not confidence (AO/ANC) experts show the final situation of inoperability in infrastructures in minimum value and finally the group of absolutely optimistic and absolutely confidence (AO/AC), generates matrices *A* with less final perturbation.

Briefly from Fig. 7, if we move from case 1 to case 4, sensitivity analysis on matrix *A* changes shows the final situation of system in a better situation with less perturbation. The importance of this analysis is that we can measure difference between experts' opinions in construction of interdependencies correlation matrix *A*, and based on that, we realize different final situations for infrastructures.

5 Conclusion

Infrastructures of developing countries are among the most considerable factors in the economic growth. Due to increasing advancement of knowledge and technology, infrastructures have also developed and became interdependent. Interdependency of infrastructures helps them to be more efficient; however, it could complicate the management of such infrastructures. Therefore, partial or complete inoperability of infrastructure could affect other infrastructures. In this paper, we applied the FIIM to estimate the final status of the system after the occurrence of natural hazards. For this purpose, we used questionnaires and opinion of experts to determine the fuzzy interdependency matrix required in the IIM. We considered the possible mistakes of experts. To do this, we introduced level of optimism and confidence levels and conducted a sensitivity analysis for questionnaires to figure out how the final status of a system would vary regarding these criteria.

To evaluate the proposed procedure, we asked 25 experts to complete the questionnaires. Then, we created the initial fuzzy interdependency matrix. We also introduced five levels for each of risk and confidence levels and calculated the relevant fuzzy interdependency matrices to each of these levels. Finally, we deffuzified the fuzzy interdependency matrices and evaluated it with the IIM to estimate the final status of the system. The computational results showed that the difference in the opinion of experts would affect the final status of the system about 26% and that final status of the system would be deteriorated when we move from AO toward AP risk levels. On the other hand, the final status of the system would also become more consistent when we move from AC toward ANC confidence levels in AP and P risk levels. But in AO and O risk levels, the final status of the system would be deteriorated when we move from AC toward ANC confidence levels.

At the time of disaster, the types of damage on infrastructures are: (1) damages that occur directly from the disaster itself (C) and (2) damages that are subsequently added to damages type (1) due to the existence of internal relationships between subsystems (cascading phenomenon). The sum of the above two factors indicates the total non-functionality of a system or infrastructure. A decision maker who controls a system is interested in predicting the failure of the system under control in the event of a disaster. This requires a comprehensive database of the types of disasters, their severity, the extent of the damages, as well as the degree of communication between the components of the system and the severity of their dependence on each other. In developing countries where this information is not available, managers lack a clear understanding of the consequences of events that may threaten them. In such a situation, this research offers the following capabilities to decision makers:

- Since there is no database to record the severity of the initial damage (C) and its associated final damage, it is possible to model all situations considered as primary damage (C) to see the final status of the system.
- In the absence of reliable data using expert opinion, we calculated the dependency matrix of system components (A) and because of the inaccuracy of this method (expert opinion), sensitivity analysis is also performed in two dimensions (optimistic/pessimistic) of expert opinion as well as (confidence/non-confidence) level of expert opinion. This sensitivity analysis will have an impact on the expert's final decision making, as it presents different scenarios. For example, an optimistic high-confidence (AO/AC) may not report the system as critical, while a high-confidence optimistic look (AP/AC) will report the critical state of the same system as critical. Obviously, these two situations will have different consequences for decision makers.
- Identifying the severity of both infrastructures' interdependence helps the decision maker to better understand the infrastructure. For example, suppose infrastructure A (which is the most influential and important system infrastructure) is more dependent on infrastructure B than any other infrastructure. This means that decision makers should pay more attention to infrastructure B than to other infrastructures to better support infrastructure A.
- Figures 3 and 4 illustrate the initial and final state of the infrastructure showing that if the initial infrastructure failure intensity changes uniformly (C), their ultimate damage resulting from the cascade phenomenon will increase linearly and uniformly, and in the meantime, impressive infrastructure has suffered the most damage growth. If one of these affected infrastructures is a key system infrastructure, management should seek to reduce its dependence on other infrastructures in order to increase the reliability of its system.

One of the limitations of the simplified approach is that the present study did not address the inherent distribution of each infrastructure and it is assumed that each infrastructure is operating normally under normal conditions, and it only deals with the perturbations between infrastructures. Also because of the unique nature of each flood occurrence, previous flood information cannot be accurately used in subsequent floods. In addition, flood happening times (during the day or night), duration of floods (from start to finish), severity of floods, infrastructure vulnerability, flood preparedness and consequences (the facilities preparation) and the accuracy of predicting climate change make it less likely to accurately predict initial damage. Therefore, the above factors are limitations of the present research approach, some of them such as the degree of optimism and the level of confidence, sensitivity analysis has been subjectively and indirectly analyzed in terms of infrastructure perturbation. Factors such as severity of flood, duration of flood, and time of occurrence can be estimated based on the amount of disruption. But factors such as flood preparedness strategies can be addressed in the future research. For example, factors such as severity of occurrence, duration of occurrence (over 3 h), and occurrence of disruption (over night or day) can cause further disruption to the infrastructure, leading to various degrees of disruption for each of the building and infrastructure.

This type of simplified analysis needs further detailed research in future. In addition, for future research, the proposed model can be evaluated under dynamic condition. By this means, recovery of infrastructures and required budget can be analyzed for a different time interval. Moreover, selection of efficient response strategies and risks in recovery time is another interesting area for future research.

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