

A resilience optimization model for transportation networks under disasters

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Abstract Natural and/or man-made disasters have caused serious problems in transportation systems due to their unpredictable and destructive characteristics. Under disasters, transportation infrastructure plays an important role in emergency management; however, this infrastructure is also vulnerable because of disasters. One way to describe the vulnerable is through resilience. Resilience refers to the ability to recover from a disruption under unexpected conditions, such as natural and/or man-made disasters. How to enhance resilience of transportation infrastructure under disasters is an important issue when facing natural or man-made disasters. This study aims to measure and optimize transportation resilience under disasters. An optimization model for resilience under the constraints of budget and traversal time is proposed. One special feature is that preparedness and recovery activities are implicitly considered and incorporated within the optimization model. The mathematical model provides a good connection between preparedness/recovery activities and network-level resilience. In order to illustrate the proposed model, a real city network and assumptions on activities of emergency management are used in a series of numerical experiments. Traffic conditions before and after disasters are evaluated by the simulation-assignment model, DynaTAIWAN. Experiments and results illustrate advantages for network-level transportation resilience assessment and also prioritize preparedness and recovery activities under budget constraints.

Keywords Resilience · Climate change · Resilience assessment

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1 Introduction

Natural and/or man-made disasters have caused serious problems in transportation systems due to their unpredictable and destructive characteristics, for example, Hurricane Katrina, which hit the USA in 2005; Sichuan Earthquake in China, which caused the number of casualties about 68,000 in 2008; Typhoon Morakot, which caused widespread devastation across southern Taiwan in 2009; and the earthquake and tsunami in Japan in 2011.

Under disasters, transportation infrastructure plays an important role in emergency management; however, the infrastructure is also vulnerable because of disasters. Vulnerability is “qualitative or quantitative expression of the level to which an entity, asset, system, network, or geographic area is susceptible to harm when it experiences a hazard” (2010 Department of Homeland Security Risk Lexicon, <http://www.dhs.gov/dhs-risk-lexicon>).

One way to describe the vulnerable is through resilience. Resilience is the ability to recover from a disruption under unexpected conditions and catastrophic failure (Turnquist and Vugrin 2013). Resilience is an integrated indicator to describe system performance under unusual conditions, recovery speed and the amount of outside assistance required to restore the system back to normal conditions (Murray-Tuite 2006). In order to enhance transportation resilience, the concept of resilience needs to be quantified and resilience can thus be measured and assessed. Resilience assessment can be used to prioritize possible preparedness and recovery activities. Although resilience has been studied in different fields, there is still no universal agreement on how to quantify transportation resilience.

This study aims to measure and optimize transportation resilience under disasters. An optimization model for resilience under the constraints of budget and traversal time is proposed. One special feature is that preparedness and recovery activities are implicitly considered and incorporated within the optimization model. The mathematical model provides a good connection between preparedness/recovery activities and network-level resilience. In order to illustrate the proposed model, a real city network and assumptions on activities of emergency management are used in a series of numerical experiments. Traffic conditions before and after disasters are evaluated by the simulation-assignment model, DynaTAIWAN (Liao et al. 2010).

Contributions of the paper include (1) resilience is defined quantitatively, and (2) an optimization model for resilience under the constraints of budget and traversal time is formulated.

The rest of this paper is organized as follows. Section 2 reviews related literature in this research. Section 3 describes the proposed model formulation. Section 4 presents numerical analysis for a real-world network to illustrate the proposed model. The conclusions are summarized in Sect. 5.

2 Literature review

Resilience is a relatively new field of research, and it has generated much interest in different fields, such as biology, sociology, economy, human community and industrial system. However, transportation resilience has been addressed only to a limited degree. In this section, topics including definitions and measure methods of resilience are reviewed. Section 2.1 reviews the concepts of resilience. Section 2.2 reviews transportation

resilience. Section 2.3 reviews quantitative measures of resilience. Section 2.4 provides a brief summary.

2.1 Concepts of resilience

Resilience concepts are useful to evaluate systems and to protect against disruptions or to accelerate recovery after external shocks. The definition of resilience varies by discipline and applications. Some researches have defined resilience in different domains and areas. The basic concept of resilience was first proposed by Holling (1973) in the field of ecology: “resilience determines the persistence of relationships within a system and is a measure of the ability of these systems to absorb change of state variable, driving variables, and parameters.” The Multidisciplinary Center for Earthquake Engineering Research (MCEER) (2005) defined resilience as: “the ability of the system to perform during and after a hazard, as well as through emergency response and strategies that effectively cope with and contain losses and recovery strategies that are able to return to levels of pre-disaster functioning as rapidly as possible.”

To examine the determinants of resilience, MCEER researchers developed R4 framework of resilience: “robustness is the ability to withstand disaster forces without significant loss of performance; redundancy is the capability of satisfying functional requirements, if significant loss of functionality occurs; resourcefulness is the ability to diagnose problems and to initiate solutions; and rapidity is the capacity to restore system operation in a timely way, containing losses and avoiding disruptions.” The US National Science and Technology Council (2005) have defined resilience as: “the capacity of a system, community, or society potentially exposed to hazards to adapt, by resisting or changing, in order to reach and maintain an acceptable level of functioning and structure. This is determined by the degree to which the social system is capable of organizing itself to increase its capacity for learning from past disasters for better future protection and to improve risk reduction measures.”

The resilience alliance (www.resalliance.org) views resilience in linked human and natural systems as involving three defining characteristics:

- (1) The amount of change the system can undergo and still retain the same controls on function and structure.
- (2) The degree to which the system is capable of self-organization.
- (3) The ability to build and increase the capacity for learning and adaptation.

The performance of a system or infrastructure is likely to change when facing an external shock. Tierney and Bruneau (2007) proposed the concept of “resilience triangle” (Fig. 1), which illustrates the loss of functionality from damage as well as the pattern of recovery over time. The depth of the triangle shows the degree of damage, and the length of the triangle shows the time to recover to normalcy.

Based on the concept of engineering resilience proposed by Holling (1973) and McDaniels et al. (2008) developed a conceptual framework of resilience in infrastructure systems considering two dimensions: robustness (the extent of system function that is maintained) and rapidity (the time required to return to full system operations and productivity). McDaniels et al. (2008) proposed to measure resilience with reference to some level of system performance.

Resilience can be expressed on the basis of performance evolution, as shown in Fig. 2. The baseline in the figure represents the original status condition, and the minimum acceptable threshold indicates an acceptable safety level for planner and operators. E_i is the

Fig. 1 Resilience triangle
(Source: Tierney and Bruneau 2007)

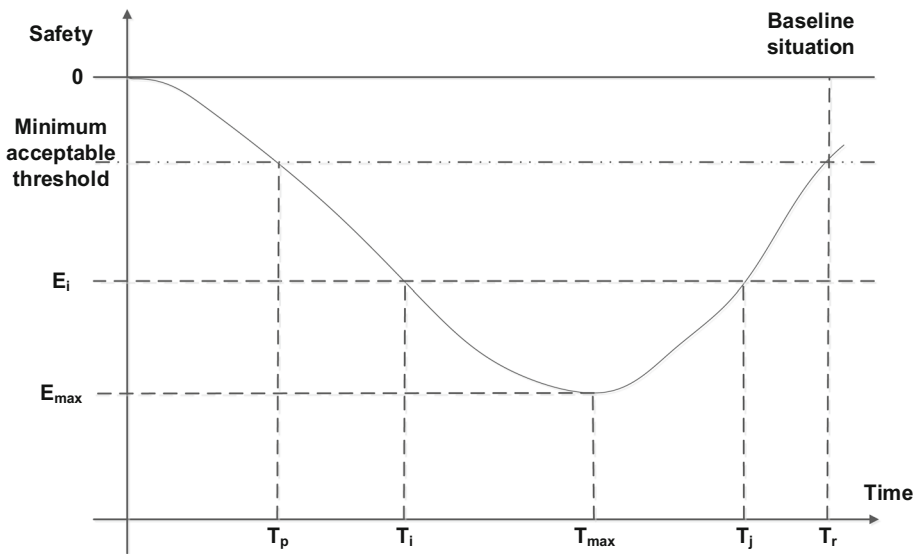
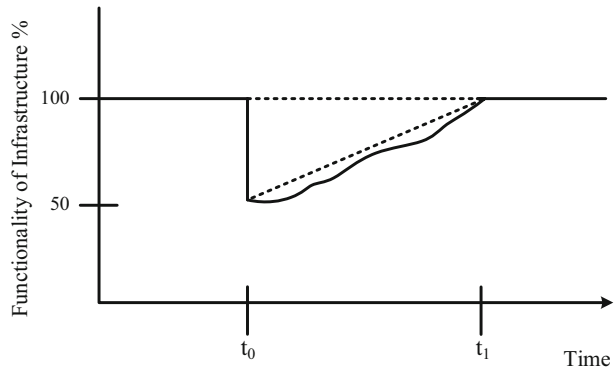


Fig. 2 Performance evolution. Source: Enjalbert et al. (2011)

amplitude of the effect of disturbance on safety at time T_i , and E_{max} is the maximum amplitude of the effect of disturbance on safety (Enjalbert et al. 2011). System resilience assessment requires two basic indexes, time interval and performance index. The time interval indicates the change of the performance and the performance index is related to the consequence of human actions.

2.2 Transportation resilience

Based on previous research, a resilient transportation system possesses the following properties: redundancy, efficiency, diversity, strength, adaptability, autonomous components, collaboration (Godschalk 2003), mobility, safety, and the ability to recover quickly (Murray-Tuite 2006). Properties of transportation resilience are summarized in Table 1.

Reggiani (2013) discussed the relationship between resilience and transportation; different resilience measures and definitions of resilience were reviewed to propose a general

Table 1 Properties of transportation resilience

Property	Definition
Redundancy	With a number of functionally similar components so that the entire system does not fail when one component fails
Efficiency	With a positive ratio of energy supplied to energy delivered by a dynamic system
Diversity	With a number of functionally different components in order to protect the system against various threats
Strength	With the power to resist attack or other outside force
Adaptability	With the capacity to learn from experience and the flexibility to change
Autonomous components	With the capability to operate independently of outside control
Collaboration	With multiple opportunities and incentives for broad stakeholder participation
Mobility	With the travelers able to reach their destinations at an acceptable level of service
Safety	With the capability to not harm the users and not expose them to hazards
Recovery	With the ability to restore rapidly and with minimal outside assistance after an event occurs

conceptual framework which aims to integrate the concept of network resilience within transport security. Transportation systems are critical infrastructures for the prosperity and growth of communities (Tamvakis and Xenidis 2012). However, transportation is vulnerable to natural disasters and man-made attacks. To avoid significant damage and loss, resilience strategies are essential to reduce the probabilities of failure, the consequences of failure, or the time for recovery.

Cox et al. (2011) defined different categories for static and dynamic transportation system resilience which can be applied to decision makers within the system. To improve resilience, managing organizations also play an important role. For example, Ta et al. (2010) suggested that State Departments of Transportation (DOTs) as managers of freight transportation system (FTS) facilities and operations can take specific actions to support FTS resilience. The actions include: (a) organizational processes that improve DOT resilience; (b) information dissemination that improves enterprise resilience; and (c) modeling and informed infrastructure capacity management that improve infrastructure resilience.

2.3 Quantitative measures of resilience

Several measurements have been proposed to study the problem of assessing resilience and to apply the concept of resilience under extreme events. Some researches provided an index of resilience related to “the capability of the system to overcome failures,” and others measure “the deduction of overall system performance.”

Murray-Tuite (2006) proposed several indicators to quantify the system resilience in terms of adaptability, mobility, recovery, and safety. Two traffic assignment methods, system optimum (SO) and user equilibrium (UE), were evaluated with regard to their impacts on resilience using those indicators (3). Cox et al. (2011) used data analysis to measure the resilience of the London transportation system under the terrorist attacks of July 2005.

Ip and Wang (2009) proposed a quantificational resilience evaluation approach to analyze the resilience of transportation networks. The resilience was measured by the

weighted average number of reliable independent paths with all other city nodes in the networks. Omer et al. (2011) proposed a networked infrastructure resilience framework to assess the resilience of the road network that connects Manhattan in New York City to the rest of the regions. The resilience of the system was measured as the ratio of the travel time preceding a disruption to the travel time following a disruption. Results showed that resilience is achievable through reducing the vulnerability of the system and increasing its adaptive capacity. Adams et al. (2012) presented a methodology for estimating two composite resilience measures—reduction and recovery, and the method was illustrated by using the concept of “resilience triangle” derived from sampled truck speeds and counts under two extreme events.

Miller-Hooks et al. (2012) measured resilience of freight transportation networks under budget and level-of-service constraints, and the model was solved through a two-stage stochastic program. An example based on a US-rail-based intermodal container network is used to illustrate the proposed model and the solution algorithm. Faturechi and Miller-Hooks (2013) provided a framework for quantifying and optimizing protective actions for infrastructure systems. A general optimization formulation was proposed to determine the maximum attainable system performance levels. Resilience was measured through the performance of coping capacity, retrofit, resource availability, expansion, and response.

2.4 Summary

In summary, the previous research on resilience pointed out the importance of resilience due to the threat of natural and man-made disasters under unexpected conditions, and they have put great effort into evaluating and measuring resilience. Researchers usually propose to measure resilience with reference to level of system performance. However, no universal agreement on quantifying transportation resilience is made. The discussions on resilience assessments are still limited. This research proposes a mathematical programming model considering multiple system performances for resilience assessment under disasters.

3 Methodology

This research aims to assess transportation resilience and to develop a mathematical model for optimal resource allocation to enhance resilience. This section describes the problem statement, research assumptions, resilience index, and mathematical model formulations.

3.1 Problem statement and research framework

Transportation infrastructures are vulnerable when facing extreme events, such as natural disasters and terrorist attacks. To enhance its ability to absorb external shocks and to recover rapidly within a given time period, it is necessary to develop resilience assessment and disaster plans including preparedness actions and recovery actions.

The conceptual framework of resilience improvement is presented in Fig. 3. Data, including impact of disaster, resilience indexes, and preparedness and recovery actions, are collected to formulate the mathematical model. During disasters, transportation system performance deteriorates, and system resilience can be enhanced through pre-disaster and post-disaster actions. The optimization model measuring transportation network resilience

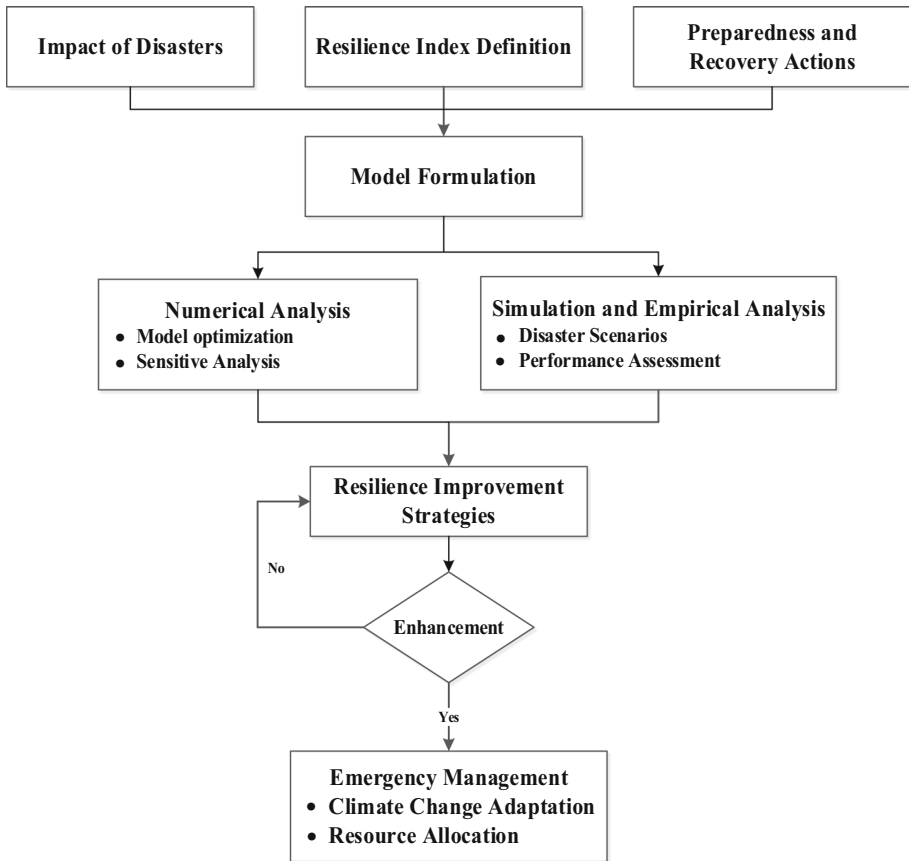


Fig. 3 Research framework

is formulated based on the above concept, and then, the model is solved by LINGO 11.0. Numerical experiments based on a real city network are conducted, and system performance is evaluated through DynaTAIWAN under different disaster scenarios. The resilience optimization model formulated in this research is applied to illustrate the process of resilience assessment and resource allocation under disasters.

In this research, the problem of resilience assessment and resource allocation is formulated as the resilience optimization model. The assumptions for the problem of resilience assessment and resource allocation are summarized as follows.

- (1) The network and disaster data are known in advance.
- (2) There are four stages in the performance response process following the disaster occurrence: Stage 1 is the occurrence of disaster; Stage 2 is reached when the max damage propagation is caused; Stage 3 is a gradual process of system recovery; and Stage 4 is the achievement of full recovery. Each time interval between stages is assumed to be equal. In practice, the time intervals between stages should depend on the time required for each process; however, the complexity of the problem becomes extremely difficult. In addition, the mathematical program is constructed based on the time intervals, and the problem cannot be solved if the intervals are unknown.

- (3) Two kinds of human activities can be implemented under disasters. One is the preparedness action taken pre-disaster, and the other is the recovery action taken post-disaster. The recovery actions are more effective than the preparedness actions since under post-disaster conditions, one can collect specific data of damage caused by disasters and can develop suitable management to quickly response to the emergency situation.

3.2 Resilience index

Among ten properties of transportation resilience described in Sect. 2, redundancy, efficiency, adaptability, mobility, and recovery are quantitative performance indicators, while the others are often classified as qualitative indicators.

In this research, the resilience index (RI) is presented as the expected mean of the ratio of the area between the real performance curve and the time axis to the area between the target performance curve and the time axis during a given time period (Fig. 4). In Eq. (1), RI is equal to the expected mean of an integral, and the integral calculates the ratio of areas with respect to time. $AP(t)$ and $TP(t)$ represent the actual performance and the target performance curves, respectively. Actually, the function value depends on factors, such as disaster types, disaster duration, and disaster severity. Theoretically speaking, these two functions can be simulated through the deployment of random function. This resilience index differs from existing ones in that it can incorporate multiple system performance measurements.

The resilience index is shown in function (1):

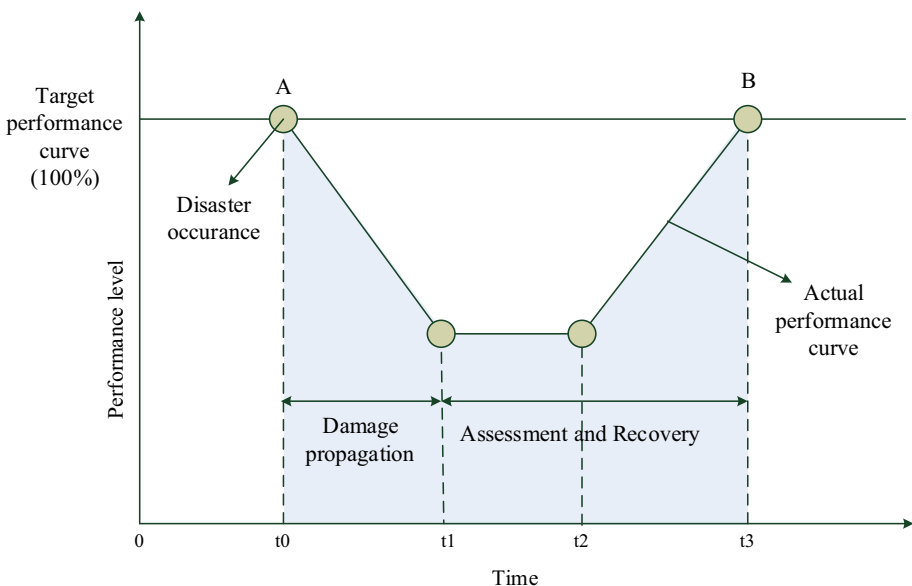


Fig. 4 A typical system performance response curve following disasters. *Source:* Ouyang et al. (2012)

$$RI = E \left[\int_0^T \frac{AP(t)}{TP(t)} dt \right] \tag{1}$$

where $AP(t)$ is the actual performance function curve, $TP(t)$ the target performance function curve, T a given time interval from the disaster occurrence to the complete restoration of the system performance.

In this research, the actual performance function curve is separated into four parts, which are based on the research assumptions mentioned in Sect. 3.1. The corresponding time interval of each stages following the disaster occurrence is assumed to be equal. The quantitative performance indicators are proposed to measure the resilience performance in a mathematical way. A general framework showing the overall concept involved in the resilience optimization model is presented, as shown in Fig. 5.

Under disaster situations, the function of transportation infrastructure is influenced, and the performance level of the network system decreases. Three performance measurements, including coping capacity, robustness, and flexibility, are assessed to evaluate transportation resilience. In this research, the three measurements are assessed and the resource optimal model is determined through coping capacity.

Flexibility is used to describe a system’s adaptive capabilities to respond to disruption (Faturechi and Miller-Hooks 2013). The delay time data are collected for flexibility measure. The robust is defined as a system’s ability to withstand the impact of the disaster event (Faturechi and Miller-Hooks 2013). The total travel time between O–D pairs is used to measure robustness to evaluate system redundancy of completing a trip between origins and destinations under disasters. When disaster events occur, the capacity of links within the network reduces and might result in connectivity failure between nodes. Coping capacity is measured by the network connectivity indicating the probability of completing a trip between an origin and a destination (Iida and Wakabayashi 1989). The probability is presented as the ratio of post-disaster link capacity and pre-disaster link capacity. Given a network of transportation infrastructure, let $G = (N, A)$, where N is the set of nodes and A is the set of arcs. Post-disaster network connectivity is formulated as follows:

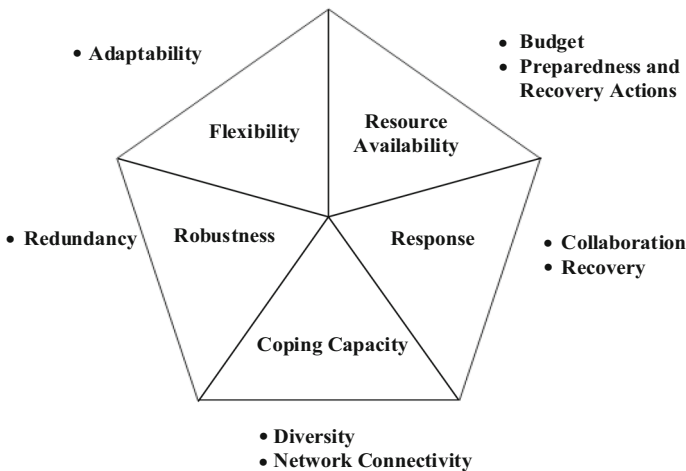


Fig. 5 General framework of the resilience optimization model

$$X_w^\xi = 1 - \prod_{k \in K_w} \left(1 - \prod_{a \in k} \frac{C_{apr}^\xi}{C_a} \right), \quad \forall k \in K_w, w \in W \quad (2)$$

where X_w^ξ is the connectivity between O–D pair w under disaster scenario ξ , W set of O–D pairs, K_w set of paths connecting O–D pair w , C_a pre-disaster capacity of arc a , C_{apr}^ξ post-disaster capacity of arc a after augmentation due to implementing preparedness action p or recovery action r under disaster scenario ξ .

3.3 Resilience optimization model

In the process of resilience assessment, the coping capacity in terms of network connectivity is evaluated in the optimization model. Robustness and flexibility of system performance is then evaluated through DynaTAIWAN simulation-assignment model based on the optimal solution of the proposed model (Liao et al. 2010). Finally, the overall resilience is obtained using the resilience index. The notations and model formulation employed for single index optimization are summarized as follows.

3.3.1 Sets

- P Set of pre-disaster preparedness actions.
- R Set of post-disaster recovery actions.
- K_w Set of paths k connecting O–D pair w .

3.3.2 Parameters

- B Given budget.
- b_{ar} Cost of implementing recovery action $r \in R$ on arc a .
- b_{ap} Cost of implementing preparedness action $p \in P$ on arc a .
- Δb_{ar}^p Cost reduction of implementing recovery action r on arc a if preparedness action p is taken.
- C_a^ξ Capacity of arc a under disaster scenario ξ .
- ΔC_{ap}^ξ Augmented capacity of arc a if preparedness action p is taken.
- ΔC_{ar}^ξ Augmented capacity of arc a if recovery action r is taken under disaster scenario ξ .
- t_w Pre-disaster traversal time between O–D pair w .
- t_w^ξ Traversal time between O–D pair w under disaster scenario ξ .
- Δt_{ar}^ξ Reduction of traversal time on arc a if recovery action r is taken under disaster scenario ξ .
- T_{\max}^w Maximum allowed traversal time between O–D pair w .
- X_w Pre-disaster connectivity between O–D pair w .
- λ_{pr} Preparedness–recovery action relationship matrix. If preparedness action p can affect recovery action r , the value is set to 1; otherwise, it is set to 0.

3.3.3 Decision variables

- β_{ap} Binary variable indicating whether preparedness action p is taken on arc a (= 1 if preparedness action p is taken and 0 otherwise).

γ_{ar}^ξ Binary variable indicating whether recovery action r is taken on arc a (= 1 if recovery action r is taken and 0 otherwise).

3.3.4 Model formulation

$$\text{Maximize } \sum_{w \in W} X_w^\xi \tag{3}$$

Subject to

$$X_w^\xi = 1 - \prod_{k \in K_w} \left(1 - \prod_{a \in k} \frac{C_{apr}^\xi}{C_a} \right), \quad \forall k \in K_w, w \in W \tag{4}$$

$$C_{apr}^\xi = C_a^\xi + \sum_p \Delta C_{ap} \beta_{ap} + \sum_r \Delta C_{ar}^\xi \gamma_{ar}^\xi, \quad \forall a \in A \tag{5}$$

$$C_{apr}^\xi \leq C_a, \quad \forall a \in A \tag{6}$$

$$0 \leq X_w^\xi \leq 1, \quad \forall w \in W \tag{7}$$

$$t_w^\xi - \sum_{a \in k} \sum_r \Delta t_{ar}^\xi \gamma_{ar}^\xi \leq T_{\max}^w, \quad \forall k \in K_w, w \in W \tag{8}$$

$$\sum_a \sum_p b_{ap} \beta_{ap} + \sum_a \sum_r b_{ar} \gamma_{ar}^\xi - \sum_a \sum_r \sum_p \Delta b_{ar}^p \lambda_{pr} \beta_{ap} \gamma_{ar}^\xi \leq B \tag{9}$$

$$\sum_p \beta_{ap} \leq 1, \quad \forall a \in A \tag{10}$$

$$\sum_r \gamma_{ar}^\xi \leq 1, \quad \forall a \in A \tag{11}$$

$$\beta_{ap} \in \{0, 1\}, \quad \forall a \in A, p \in P \tag{12}$$

$$\gamma_{ar}^\xi \in \{0, 1\}, \quad \forall a \in A, r \in R \tag{13}$$

The decision variables are the binary variables indicating whether preparedness and recovery actions are taken. The post-disaster capacity can be augmented by taking preparedness or recovery actions, while the post-disaster traversal time can be reduced by implementing recovery actions. The difference is presumed based on the research assumption. Objective function (3) maximizes the network connectivity between O–D pairs. Constraint (4) is the function of the connectivity between O–D pairs under disasters. Constraint (5) is used for changing arc capacity under preparedness and recovery actions. Augmented capacity ΔC_{ap} and ΔC_{ar} is assumed to be achieved by taking preparedness actions $p \in P$ and recovery actions $r \in R$, respectively. Constraint (6) limits the augmented post-disaster capacity of arc a to not exceed the pre-disaster capacity of arc a .

Constraint (7) restricts the value of connectivity between 0 and 1. Constraint (8) requires the total traversal time of arc a to not exceed the maximum allowed traversal time between each O–D pair w . Constraint (9) is a budget constraint, in which the total cost does not

exceed the budget B . The interaction between pre-disaster preparedness and post-disaster recovery actions is defined by the preparedness–recovery action relationship matrix λ_{pr} . This matrix predetermines whether the recovery actions $r \in R$ are affected by preparedness actions $p \in P$ in terms of its implementation cost. That means if a preparedness action p is taken pre-disaster, the cost of implementing a relevant recovery action r can decrease, which is less than the implementation cost of recovery action r taken alone.

Constraints (10) and (11) specify that at most one set of preparedness actions and one set of recovery actions can be taken for each arc, respectively. Constraints (12) and (13) are binary variable constraints. A more detailed discussion on model formulation can be found in Ko (2014).

4 Numerical study

4.1 Network characteristics and parameter settings

Numerical experiments are conducted in a city network developed based on the Sanmin district in Kaohsiung City, the most populated district in the city. The network is depicted in Fig. 6. Three scenarios are designed to illustrate the proposed mathematical programming model for the resilience assessment and resource allocation problems.

In each scenario, 20 origin–destination (O–D) pairs are studied. In transportation planning, origins and destination refer to zone centroids and normally are only subsets of network nodes. The parameters in the experiments are set up on the basis of the result of previous numerical experiment (Ko 2014). Two levels of preparedness actions and three levels of recovery actions are available (Table 2). The cost of implementation and the impact on the arcs under different activity levels are listed in Table 3. (Note P_i represents the preparedness actions, $i = 1, 2$; R_j represents the recovery actions $j, j = 1, 2, 3$.) Other parameter settings are listed as follows:

- (1) The weight setting for the performance measures of coping capacity, robustness, and flexibility is assumed to be 1:1:1. The weights can be determined through expert questionnaire with analytical hierarchy process (AHP) in the future.
- (2) The maximum allowable traversal time for each O–D pair is assumed to be 1.5 times the pre-disaster travel time of the O–D pair.
- (3) The implementation cost of recovery actions is reduced 20% if the corresponding preparedness actions are taken.
- (4) Current traffic signal data from the Transportation Bureau of Kaohsiung City are used. The simulation time is 140 min to obtain complete simulation results of system performance under different conditions.

4.2 Scenario descriptions

Three scenarios are designed to illustrate the proposed model in solving the resource allocation and resilience assessment problems under different disasters and resource availabilities.

- (1) Scenario 1: natural disaster

Scenario 1 simulates a natural disaster, typhoon with heavy rain, in the Sanmin district. We assume that no preparedness activity is performed; therefore, the roads

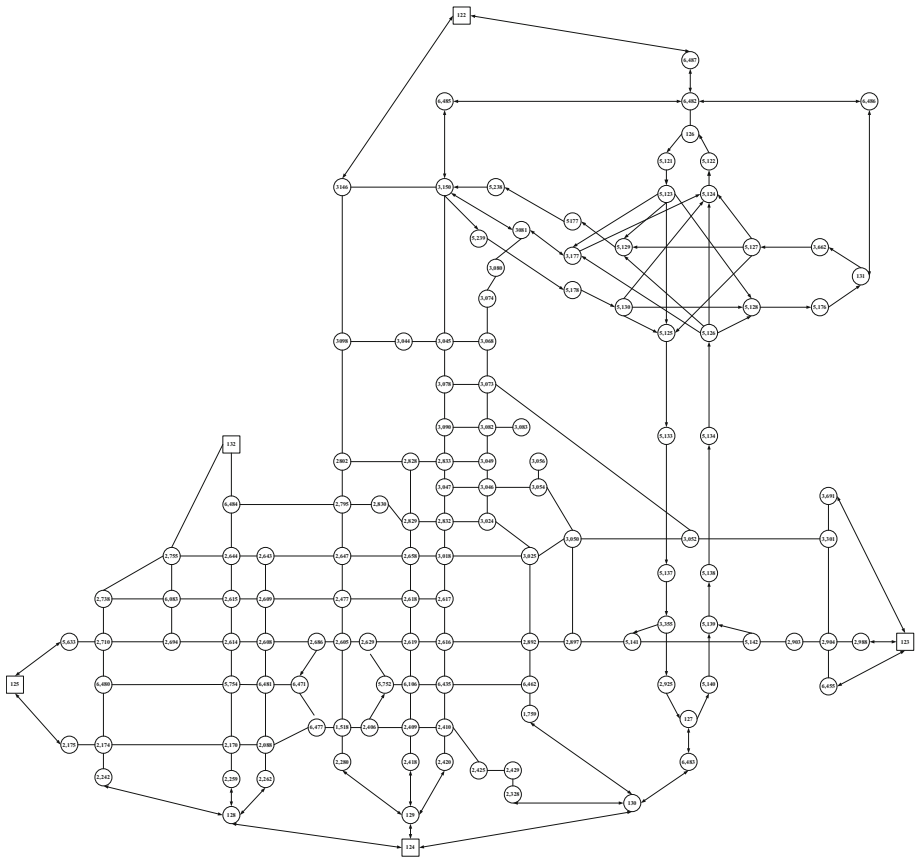


Fig. 6 The Sanmin district network in Kaohsiung City

Table 2 Summary of preparedness and recovery actions

Activity	Level	Action
Preparedness	1	Prepare possible resources for potential recovery activities
	2	Add additional links to the network
Recovery	1	Perform traffic control to the impact area
	2	Build temporary roads
	3	Repair and restore damaged infrastructure

are seriously flooded and the capacities of multiple connected roads are reduced 40%. The available budget is assumed to be 100 units for taking recovery actions. Figure 7 illustrates the geographic locations of the impact area and the affected roads in Scenario 1. The travel time and delay time matrices in Scenario 1 are summarized in Tables 4 and 5.

Table 3 Preparedness and recovery actions in empirical experiment

Activity level	Cost (unit)	Increase in link capacity (%)	Decrease in link travel time (%)	Decrease in link delay time (%)
P1	2	8	–	–
P2	3	10	–	–
R1	1	5	5	10
R2	4	10	10	15
R3	6	15	15	20

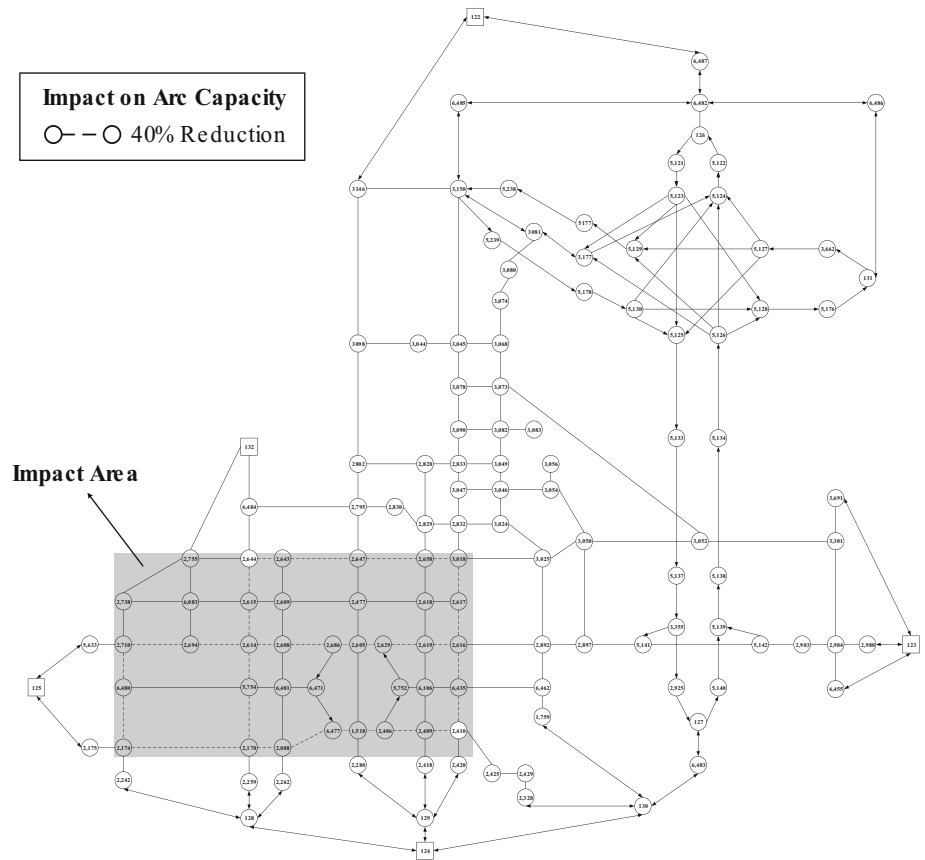


Fig. 7 Network structure for Scenarios 1

(2) Scenario 2: man-made disaster

In Scenario 2, a man-made disaster, an explosion due to a bomb attack inside a hospital, is simulated in the Sanmin district. The incident brings serious damage to the surrounding roads, especially the impact area in Fig. 8. Different levels of capacity reduction, 30, 45, and 60%, are assumed. The available budget is assumed

Table 4 Post-disaster delay time matrix of Scenario 1 (min)

O/D node	2174	2410	2644	2833	3301
2174	0.00	1.47	1.26	2.75	2.50
2410	1.85	0.00	1.91	2.22	2.88
2644	1.03	1.42	0.00	2.49	3.04
2833	1.75	1.13	1.72	0.00	1.49
3301	3.70	3.34	4.43	3.82	0.00

Table 5 Travel time matrix of Scenario 1 (min)

O/D node	2174	2410	2644	2833	3301
Pre-disaster					
2174	0.00	4.42	2.64	5.40	9.06
2410	4.42	0.00	3.72	2.51	4.79
2644	2.64	3.72	0.00	2.76	7.61
2833	5.40	2.51	2.76	0.00	5.81
3301	9.22	4.79	7.61	5.81	0.00
Post-disaster					
2174	0.00	6.69	4.56	8.13	14.10
2410	6.93	0.00	5.98	4.22	8.47
2644	4.30	5.69	0.00	4.64	11.58
2833	9.36	4.11	4.36	0.00	8.96
3301	14.13	8.46	11.69	9.01	0.00

to be 100 units. Both preparedness and recovery actions are available. The travel time and delay time matrices in Scenario 2 are summarized in Tables 6 and 7.

(3) Scenario 3

Scenario 3 is similar to Scenario 2, but with more budget. We also assume that only recovery actions are considered because the government is not aware of the bomb attack. The budget is assumed to be 200 units.

4.3 Result analysis

The results include (1) the values of resilience, (2) the system performance of coping capacity, robustness, and flexibility, and (3) optimal budget allocations and recommended actions. The experiment results of each scenario are discussed, respectively.

(1) Results of Scenario 1

The results in Scenario 1 are summarized in Table 8. The network resilience is 0.74 under the flood disaster. This shows that the overall network performance can maintain about 75% during the disaster. However, in comparison with the target resilience level of 1.0, there is still room for improvement. The performance response curve from Stage 1 to Stage 4 is shown in Fig. 9. The system performance decreases to 57% after the shock of disaster and returns back to 70%. Recommended actions include R1 (perform traffic control) and R3 (repair and restore damaged roads). Since more resource is allocated on repairing, the results show that R3 is more effective under limited budgets.

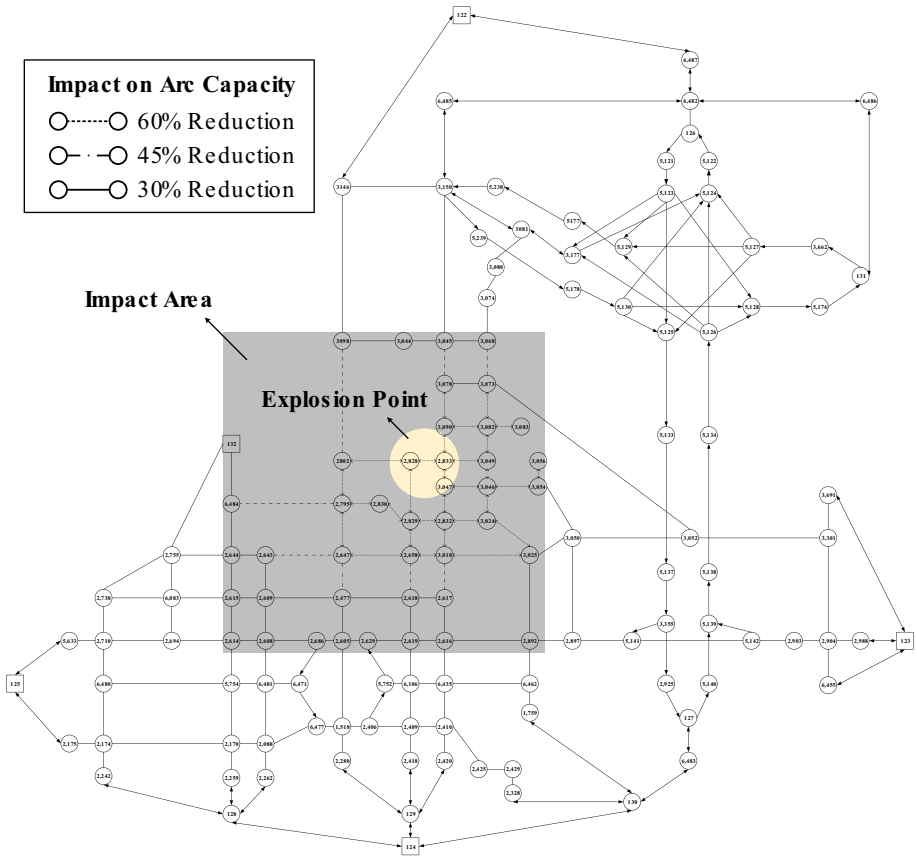


Fig. 8 Network structure for Scenarios 2 and 3

Table 6 Post-disaster delay time matrix of Scenarios 2 and 3 (min)

O/D node	2174	2644	2892	3081	3301
2174	0.00	0.66	1.39	3.42	3.91
2644	0.56	0.00	2.20	2.75	3.24
2892	1.35	1.97	0.00	2.68	1.02
3081	3.48	2.38	2.62	0.00	1.65
3301	3.83	3.53	0.94	1.57	0.00

(2) Results of Scenario 2

The network resilience is 0.78 under the bomb disaster. The results indicate that the network can maintain 78% of the overall performance under the disaster. The average system performance levels of coping capacity, robustness, and flexibility are shown in Table 9. Flexibility is the highest. The performance response curve from Stage 1 to Stage 4 is shown in Fig. 10. The performance level at Stage 2 drops to 63%, and the system performance recovers to 70% after implementing a set of actions. As shown in Table 9, the recommended actions include P1, R1, R2, and R3. One can preposition resources in anticipation of potential recovery activities on

Table 7 Pre-disaster travel time matrix of Scenarios 2 and 3 (min)

O/D node	2174	2644	2892	3081	3301
Pre-disaster					
2174	0.00	2.64	6.78	11.32	9.06
2644	2.64	0.00	5.59	9.23	7.61
2892	6.73	5.31	0.00	4.55	6.03
3081	11.68	9.44	4.94	0.00	6.14
3301	9.22	7.61	6.33	7.60	0.00
Post-disaster					
2174	0.00	6.69	4.56	8.13	14.10
2644	6.93	0.00	5.98	4.22	8.47
2892	4.30	5.69	0.00	4.64	11.58
3081	9.36	4.11	4.36	0.00	8.96
3301	14.13	8.46	11.69	9.01	0.00

Table 8 Results of Scenario 1

Network resilience	0.75	
Average system performance level	Coping capacity	0.56
	Robustness	0.76
	Flexibility	0.58
Recovery actions selected	$\gamma_{71}, \gamma_{83}, \gamma_{93}, \gamma_{103}, \gamma_{133}, \gamma_{143}, \gamma_{151}, \gamma_{161}, \gamma_{173}, \gamma_{183}, \gamma_{213}, \gamma_{223}, \gamma_{231}, \gamma_{241}, \gamma_{333}, \gamma_{341}, \gamma_{353}, \gamma_{361}, \gamma_{373}, \gamma_{381}, \gamma_{471}, \gamma_{483}, \gamma_{503}, \gamma_{523}$	
The proportion of cost (recovery action)	Level 1	8.6%
	Level 2	0
	Level 3	91.4%

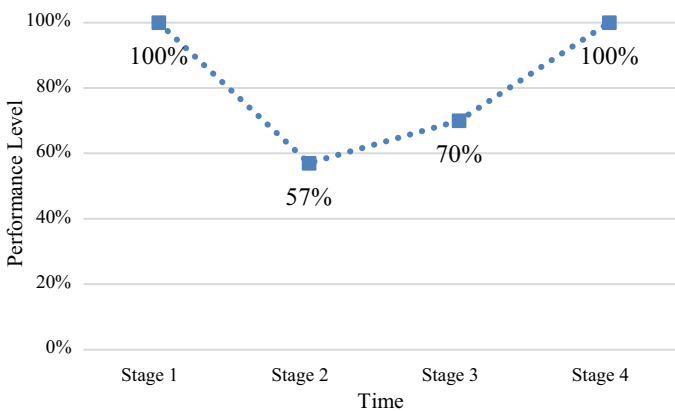


Fig. 9 Performance response curve of Scenario 1

Table 9 Results of Scenario 2

Network resilience	0.78	
Average system performance level	Coping capacity	0.49
	Robustness	0.83
	Flexibility	0.67
Actions selected		
Preparedness action	$\beta_{31}, \beta_{41}, \beta_{51}, \beta_{61}, \beta_{81}, \beta_{131}, \beta_{151}, \beta_{161}, \beta_{431}, \beta_{441}, \beta_{451}, \beta_{461}, \beta_{471}, \beta_{481}, \beta_{491}, \beta_{501}$	
Recovery action	$\gamma_{33}, \gamma_{41}, \gamma_{61}, \gamma_{81}, \gamma_{93}, \gamma_{103}, \gamma_{111}, \gamma_{132}, \gamma_{141}, \gamma_{153}, \gamma_{163}, \gamma_{321}, \gamma_{331}, \gamma_{341}, \gamma_{352}, \gamma_{361}, \gamma_{433}, \gamma_{443}, \gamma_{453}, \gamma_{463}, \gamma_{473}, \gamma_{483}, \gamma_{493}, \gamma_{503}$	
The proportion of cost		
Preparedness action	Level 1	25.2%
	Level 2	0
Recovery action	Level 1	7.1%
	Level 2	6.3%
	Level 3	61.4%

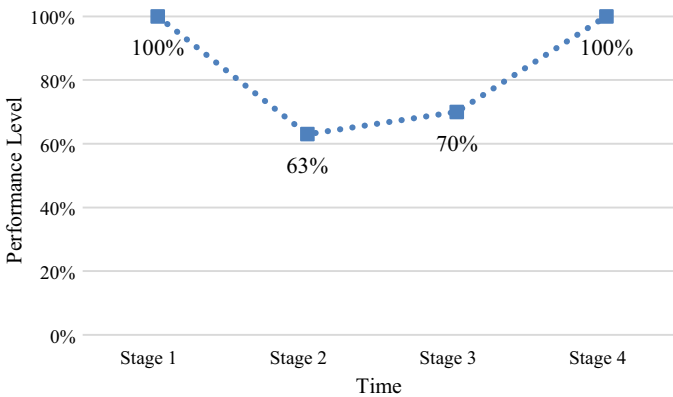


Fig. 10 Performance response curve of Scenario 2

several roads for disaster prevention. During disaster periods, recovery actions including traffic controls, temporary roads, and repairing damaged infrastructure, and more resources are allocated in R3 (61.4% of budget).

(2) Results of Scenario 3

The network resilience is 0.73 under Scenario 3. Compared with Scenario 2, there is a 5% decrease on the overall resilience level due to the limited effect of recovery actions on arc capacity augmentation. However, under the same limited budget levels, better resilience is obtained when both types of activities are taken. The average system performance of coping capacity, robustness, and flexibility is shown in Table 10. Among the three of them, robustness is the highest, while coping capacity is the lowest. Compared with the performance response curve under Scenario 2, the system performance at Stage 2 is lower under Scenario 3. Larger damage degree is caused at Stage 2 after the occurrence of disaster under Scenario 3;

Table 10 Results of Scenario 3

Network resilience	0.73	
Average system performance level	Coping capacity	0.33
	Robustness	0.82
	Flexibility	0.62
Recovery actions selected	$\gamma_{33}, \gamma_{43}, \gamma_{53}, \gamma_{63}, \gamma_{73}, \gamma_{83}, \gamma_{93}, \gamma_{103}, \gamma_{113}, \gamma_{123}, \gamma_{133}, \gamma_{143}, \gamma_{153}, \gamma_{163},$ $\gamma_{253}, \gamma_{263}, \gamma_{313}, \gamma_{323}, \gamma_{333}, \gamma_{343}, \gamma_{353}, \gamma_{363}, \gamma_{433}, \gamma_{443}, \gamma_{453}, \gamma_{463},$ $\gamma_{473}, \gamma_{483}, \gamma_{493}, \gamma_{503}, \gamma_{553}, \gamma_{563}$	
The proportion of cost (recovery action)	Level 1	0
	Level 2	0
	Level 3	100%

on the other hand, better recovery at Stage 3 is found under Scenario 3 due to the increase in budget (Fig. 11). According to the result, all the budget is spent on the most effective action level, R3.

4.4 Computational performance

In terms of computational performance, two major tasks are (1) data preparation from simulation model and (2) mathematical program solution. The computation time for DynaTAIWAN is about 60 CPU seconds, and the second part is less than 1 CPU second. DynaTAIWAN, as a simulation-assignment model, generates simulation results based on some random functions, and the stability of the simulation results is described in Liao et al. (2010). LINGO is a commercial software for math programs (<https://www.lindo.com/index.php/products/lingo-and-optimization-modeling>).

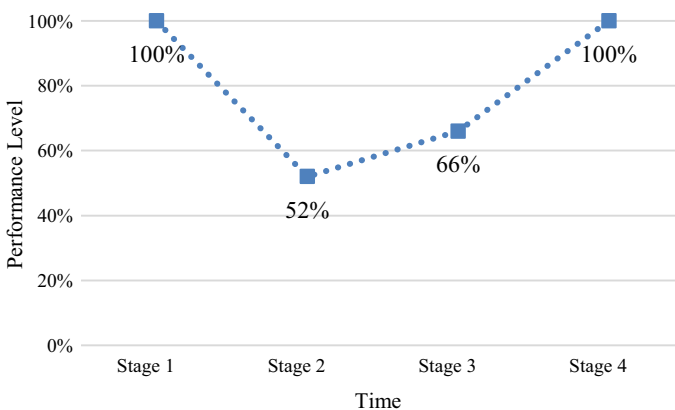


Fig. 11 Performance response curve of Scenario 3

5 Conclusions

This research proposes a mathematical model for network resilience assessment and resource allocation under disasters. The model aims to determine the resource allocation of preparedness and recovery activities and to evaluate the network resilience under disaster situations. The proposed model is capable of measuring the ability of network systems to absorb external shocks and recover to the original performance level through resilience improvement actions.

The Sanmin district in Kaohsiung City is selected as the demonstrative area in the empirical experiments. Three scenarios are designed to discuss the resilience assessment and resource allocation problem under disaster conditions. Scenario 1 simulates the resilience assessment and resource allocation under a flood disaster. Scenario 2 and Scenario 3 simulate a man-made disaster with different resource arrangements. The results indicate that the availability of budget and implementation activities plays an important role in enhancing resilience.

This research suggests that the Kaohsiung City Government should consider the concept of resilience in transportation planning including transportation planning steps for long-term plans and network performance improvement strategies for short-term management. Furthermore, constructing a disaster database is suggested to make disaster prevention enforcement plans and cope with disasters during emergency situations. The authors recommend constructing a disaster database in order to make disaster prevention enforcement plans and cope with disasters. For future study, specific data should be collected, including network travel time, actions and costs of preparedness and recover activities, and the damage degree of roads.

Future developments include (1) multiobjective formulation to consider resilience performance measurements simultaneously; (2) an AHP expert questionnaire for weights of multiple indicators can approximate weights for resilience measures for the multiobjective problems; and (3) in practice, the time intervals between stages should depend on the time required for each process; however, the complexity of the problem might become extremely difficult. How to consider flexible time intervals requires more attentions from research society.

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