Assessing the Cascading Impact of Tunnel Failures on Network Resilience

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Abstract: Taiwan is located on the Circum-Pacific Belt, where earthquakes frequently occur and pose significant threats to the structure and stability of transportation infrastructure, including roads, bridges, and tunnels. Among the infrastructure, tunnels are particularly critical due to their enclosed nature, which makes rescue and evacuation efforts much more challenging when damage occurs. This often leads to prolonged disaster relief efforts and greater cascading effects over the entire transportation system, highlighting the critical importance of enhancing tunnel resilience against natural disasters. Hence, this research aims to assess the resilience from the perspective of the overall roadway network and enhance the network's resilience by reinforcing the most critical tunnels as part of pre-disaster planning. To achieve this, a bi-level model is proposed, considering the reinforcement problem using capacity as an indicator to evaluate resilience. The results indicate that implementing reinforcement measures increases resilience and reduces total travel time against the impact of natural disasters on the roadway network.

Keywords: Tunnels, Resilience, Network, Cascading effects

1. INTRODUCTION

Earthquakes, caused by the movement of tectonic plates, can damage the structure and stability of various infrastructures and may even directly lead to their collapse. Additionally, extreme weather events such as typhoons, heavy rainfall, and tsunamis can trigger landslides and mudflows, further weakening the foundation stability of critical infrastructures and making them more prone to collapse. These natural disasters pose severe threats to the safety of residents and their properties. From the perspective of roadway network management, critical transportation infrastructure components, such as roads, bridges, and tunnels, are particularly vulnerable to disasters. Once a disaster occurs, in addition to emergency repair and the construction of alternative routes, identifying the most severely affected roads in advance would allow for pre-disaster reinforcement, helping minimize the impact on transportation.

Taiwan is located in the Circum-Pacific seismic belt, making it particularly important to focus on preventing damage to infrastructure. Among various types of transportation infrastructures, the impact on tunnels can be especially essential and serious. Unlike roads and bridges, which can still be accessed by aerial rescue teams after being damaged, tunnels are enclosed structures. If a tunnel collapses, entry and exit become significantly more difficult, requiring more time for rescue and repair. As we can see in Figure 1, Taiwan has a large number of tunnels, with over 500 highway tunnels alone, most of which are concentrated in the eastern region, where earthquakes occur more frequently, and it is often the first frontline to the impact of typhoons as well. In some areas, a single tunnel serves as the only external route. If such a tunnel collapses, these areas can become isolated, making disaster relief even more difficult.

Additionally, when transportation infrastructure is damaged, traffic may further cascade to alternative routes, increasing the burden on other roads. This highlights the importance of regular inspections and maintenance of transportation infrastructure to ensure that the system can effectively respond to seismic challenges and maintain stable operations.

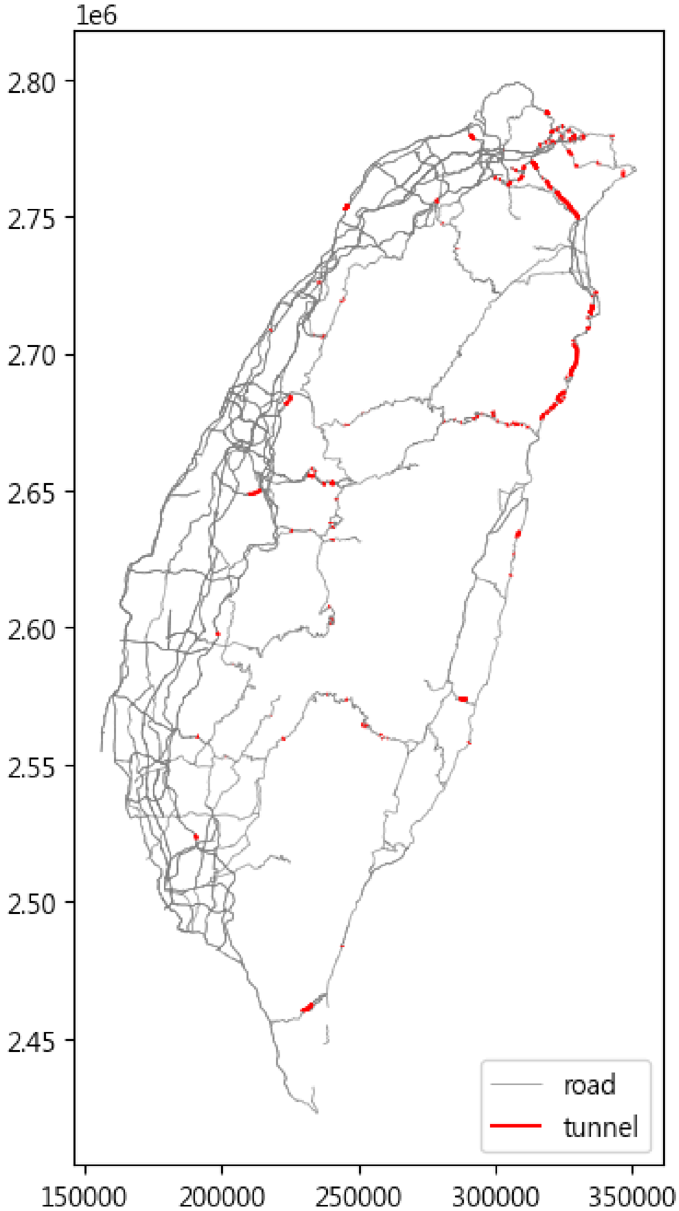

Figure 1. Distribution of Highway Tunnels in Taiwan

There are a substantial number of previous studies assessing network performance from different aspects. For example, Gu et al. (2020) used “Reliability” as the indicator to evaluate the network performance. Cimellaro et al. (2010) defined “Robustness” as the ability of a component to withstand stress before failing, which represents the remaining performance after a disaster.

The concept of “Resilience” is first proposed in Holling, C. S. (1973). From an ecological perspective, it proposed that resilience is an ability of a system to absorb changes and disturbances while still maintaining its essential functionality and structure. Bruneau et al. (2003) proposed the attributes of “4R”, which including Robustness, Redundancy, Resourcefulness, and Rapidity to define resilience. From these studies, we can see that the measurement of resilience involves the dimensional "time" throughout the process of being impacted and/or damaged. How much the performance drops and how long it takes to recover are critical in assessing the resilience of a system. For example, as illustrated in Figure 2, a system originally is operated at a performance level 10, experiences a performance drop to 7 around the time point 10 (due to the impact of a disaster), and recovers back to the original level after the time point 13. Resilience can be defined as the gray area under the performance curve. The red point in the figure indicates that the system (assuming it is a tunnel) reaches its lowest performance after being impacted. If this drop reaches a lower performance level, or it takes a longer time for the system recovers back to its original level, the gray area is smaller, indicating reduced capabilities to resist/absorb the disaster impact or recover from it.

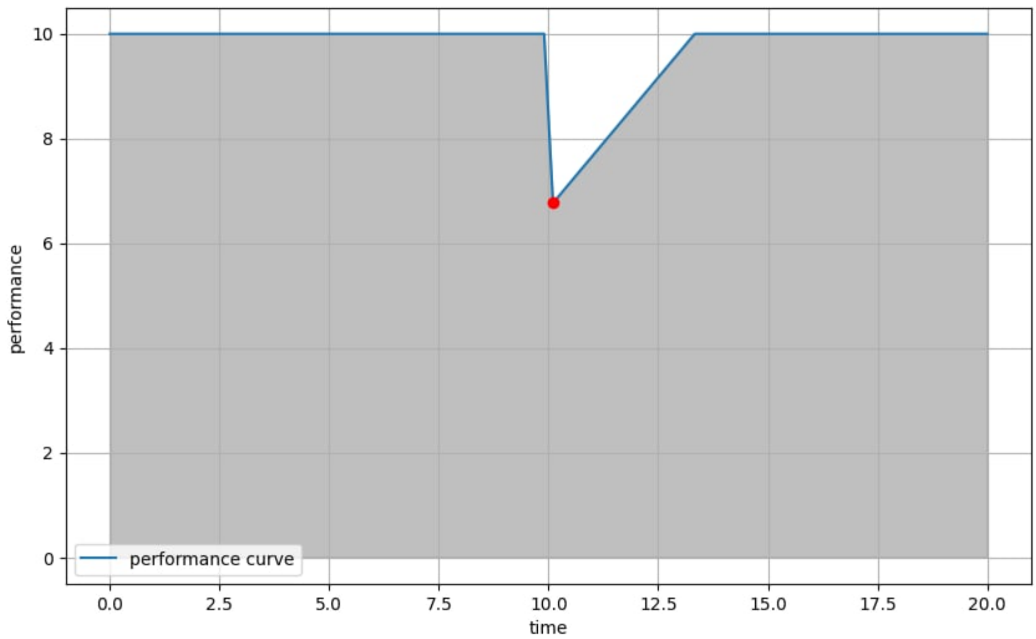

Figure 2. Illustration of performance curve and resilience calculation

Moreover, Ash & Newth (2007) suggested that the failure of a single node can alter the traffic balance within the network, leading to the redistribution of traffic to other nodes. If these nodes cannot accommodate the additional traffic, the redistribution process will occur again, manifesting the phenomenon named "cascading." To further account for such a phenomenon in the assessment of transportation system resilience and relevant decision-making to ensure system performance, this research develop a bi-level optimization model, where the upper level determines the reinforcement strategies to strengthen tunnels in a roadway network, and the lower level addresses traffic assignment over it.

The rest of the paper is organized as follows. The research framework is presented in the next section. Then, the bi-level model is proposed in the third section to optimize reinforcement strategies for tunnel strength enhancement by considering traffic flow distribution, thereby attaining system resilience maximization in a more holistic manner. The case study is then provided to illustrate the results of the proposed model. Finally, the concluding remarks are drawn, and directions for future research are suggested in the last section.

2. RESEARCH FRAMEWORK

The flow chart for the bi-level modeling research framework is illustrated as follows:

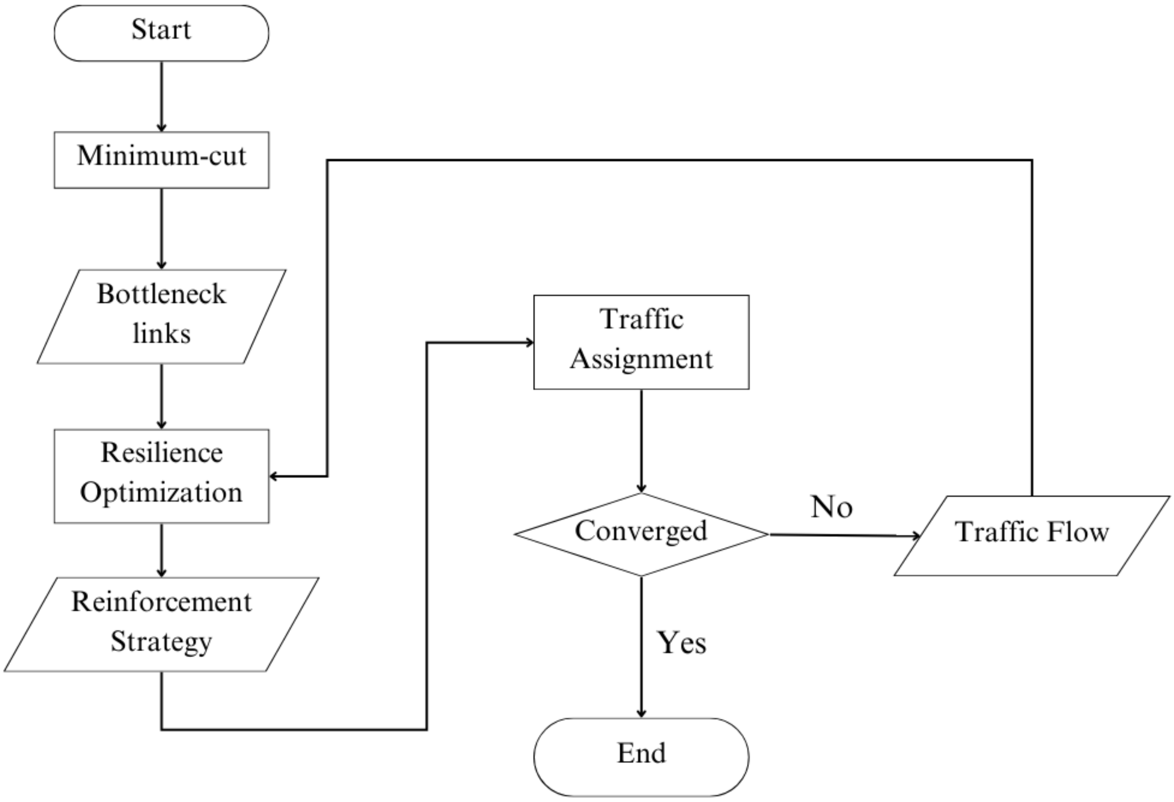

Figure 3. Flow chart of the research

In this study, the proposed research framework contains a minimum cut problem and a bi-level optimization problem. The upper level of the model is a reinforcement problem to optimize system resilience, while the lower-level model is a traffic assignment problem. We used road capacity as the indicator of assessing resilience for the reinforcement problem. The reinforcement strategies determined in upper-level model can influence the lower-level model, which updates the road network conditions for traffic flow assignment to minimize total travel time. The traffic flow pattern obtained from the lower level is then fed back to the upper level to determine the weights for selecting tunnels prioritized for reinforcement; routes (and tunnels along them) associated with higher traffic volumes are considered more critical and assigned higher weights because their disruption can affect larger traffic flows, and the cascading effects may further cause congestion over the network. Consequently, if a route is identified as critical, the tunnels along that route will be prioritized for reinforcement to reduce the risk of complete disruption and its impact.

3. METHODOLOGY

3.1 Assumptions

There are some assumptions in this study as follows:

1) This research primarily focuses on tunnel reinforcement and assumes that only tunnels

will be affected by disasters.

2) Only the degree of damage is affected when the tunnel is chosen to be reinforced, and the recovery speed remains unchanged (we focus on the pre-disaster planning of tunnel reinforcement but do not consider post-disaster response and recovery).
3) The tunnels experience the impact of the disaster simultaneously.

3.2 Minimum Cut Model

To find the tunnels that need to be reinforced, we first apply the minimum cut problem to the network to find the minimum cut over the bottleneck(s) that denotes the maximum traffic volume over and O-D (Origin-Destination) pair that the network can accommodate. In other words, if these links (identified as the bottlenecks) are damaged, or their capacities drop, the capacity if the network can be directly affected. Hence, we find the critical tunnels that need to be reinforced among the bottlenecks by applying the minimum cut problem first.

3.2.1 Notations

The network is represented as a directed graph G= (N, E). The notations in the minimum cut problem are as follows:

Table 1. Notations list in for the minimum cut problem

Sets	N	The set of nodes
	E	The set of links
	E′	The set of links in the minimum cut
Parameters	c_{ij}	The capacity of link *ij*, $(i,j) \in E$
Variables	y_{ij}	Binary variable indicating whether the link *ij* belongs to the minimum cut, $(i,j) \in E'$
	u_i	Binary variable indicating whether the node *i* is on the same side with an origin node O in contrast to the cut, $i \in$ N

3.2.2 Model development

The formulations are as follow:

$$min \sum_{(i,j)\in E} c_{ij}y_{ij} \tag{1}$$

$$u_O = 1,\ u_D = 0 \tag{2}$$

$$u_i - u_j + y_{ij} \geq 0,\ \forall(i,j) \in E \tag{3}$$

$$y_{ij} \in \{0,1\},\ \forall(i,j) \in E \tag{4}$$

$$u_i \in \{0,1\},\ \forall i \in N \tag{5}$$

The objective of the minimum cut problem is to minimize the total capacity over the minimum cut. Eq. (2) represents that the origin and destination must be on the different side of the cut. Eq. (3) denotes that if link *ij* is in the minimum cut, both nodes *i* and *j* must on the different sides of the cut set.

3.3 Upper-level Model (decisions for tunnel reinforcement)

E′, the minimum cut determined from Section 3.2, contains the set of bottleneck tunnels. Then, in the upper-level model, we further identify the tunnels from the bottlenecks, which play the most significant roles in system resilience, for reinforcement.

3.3.1 Notations

The network is represented as a directed graph G= (N, E). The notations in the upper-level model are listed as follows:

Table 2. Notations list in upper-level model

Sets	N	The set of nodes
	E	The set of links
	E′	The set of bottleneck tunnels
	W	The set of O-D pairs
	K	The set of paths
Parameters	δ_{ij}	The weight of the tunnel *ij*, $(i,j) \in E'$
	$P_{ij}(t)$	The performance curve of the unreinforced tunnel on link *ij*, $(i,j) \in E'$
	$P'_{ij}(t)$	The performance curve of the reinforced tunnel on link *ij*, $(i,j) \in E'$
	$R_k(t)$	The performance curve of the path k, $k \in$ K
	$R_w(t)$	The performance curve of the O-D pair *w*, $w \in$ W
	b	The budget of reinforcement
	f_k	The flow volume on path k, $k \in$ K
Variables	z_{ij}	Binary variable indicating whether the tunnel *ij* is reinforced, $(i,j) \in E'$
	$\alpha_{w,k,i,j}$	Binary variable indicating whether the link *ij* is on the path *k*, O-D pair *w*, $w \in$ W, $k \in$ K, $(i,j) \in$ E

3.3.2 Model development

Once the set of bottleneck tunnels in E′ is identified, we further determine the critical tunnels that should be reinforced in the attempt to optimize system resilience against natural disasters. The upper-level model for this reinforcement problem is formulated as follows:

$$\max \sum_{w} \int_{t} R_w(t) \tag{6}$$

$$\sum_{i,j} z_{ij} \le b \tag{7}$$

$$R_{w,k}(t) = min_{(i,j)\in S}\alpha_{w,k,i,j}\left(z_{ij}P'_{ij}(t) + \left(1 - z_{ij}\right)P_{ij}(t)\right) \forall k \in \mathrm{K}, w \in \mathrm{W} \tag{8}$$

$$R_w(t) = max_{(i,j)\in P}\left(\frac{f_k}{\sum_k f_k}R_k(t), \frac{f_k}{\sum_k f_k}\alpha_{w,k,i,j}\left(z_{ij}P'_{ij}(t) + \left(1 - z_{ij}\right)P_{ij}(t)\right)\right) \forall w \in \mathrm{W} \tag{9}$$

$$z_{ij} \in \{0,1\} \ \forall (i,j) \in \mathrm{E}' \tag{10}$$

$$\alpha_{w,k,i,j} \in \{0,1\} \ \forall w \in \mathrm{W}, k \in \mathrm{K}, (i,j) \in \mathrm{E} \tag{11}$$

The objective of this optimization problem, Eq. (6), is to maximize system resilience based on the calculation of the area under the performance curve (integral along the performance curve), as illustrated in Figure 2. The resilience over each O-D pair is determined by the performance curve and weighted by the associated O-D demand. Eq. (7) is the budget limit in terms of the number of tunnels that can be reinforced. We separate the calculation of resilience over parallel and series relationships between the tunnels to be reinforced in terms of their relative positions in the network structure. If there are more than one tunnels on the same path, we denote this situation as the presence of series tunnels. In Eq. (8), the path resilience is determined by the most vulnerable tunnel (most prone to collapse or capacity drop) in series tunnels. The parallel relationship means that the tunnels are on different paths for the same O-D pair. In Eq. (9), the resilience over the O-D pair depends on the tunnel with better performance (higher capacity) in the context of the parallel relationship.

3.4 Lower-level Model (traffic assignment)

The traffic assignment problem in this study is to account for the cascading effect of traffic flow (re)distribution upon the impacted network. Through the traffic assignment, we are inferring the change of the flow pattern upon the tunnel reinforcement strategies determined in the upper level.

3.4.1 Notations

The graph G= (N, E) is same as the upper-level model. The notations used in the lower-level model are as follow:

Table 3. Notations list in lower-level model

Sets	N	The set of nodes
	E	The set of links
	E′	The set of bottleneck tunnels (along the links in the minimum cut)
	W	The set of O-D pairs
Parameters	d_w	The demand on O-D pair w, $w \in$ W
	c_{ij}	The capacity of link *ij*, $(i, j) \in$ E
	t_s	The time point that the performance curve is at its lowest
Variables	f_k	The flow on path k, $k \in K$
	$t_{0_{ij}}$	The travel time based on free flow speed on link *ij*, $(i, j) \in$ E
	λ_{ijk}	Binary variable indicating whether the link *ij* is on path k, $(i, j) \in$ E, $k \in$ K
	z_{ij}	Binary variable indicating whether the tunnel *ij* is reinforced, $(i, j) \in$ E
	x_{ij}	The flow volume on link *ij*, $(i, j) \in$ E

3.4.2 Traffic assignment

To minimize the total travel time, we apply the System Optimal (SO) condition to solve the traffic assignment problem. Although the User Equilibrium (UE) may be more realistic to the travelers, it takes a certain period of time for a traffic network to attain that condition (when all travelers are familiar or have certain level of knowllink about the network). Instead, we use SO assignment in this study to present the situation upon disaster impact, which the associated authorities seek to attain by implementing management strategies for traffic flow during and/or post-disaster.

We refer to the research of Zhao and Zhang (2020). In Eq. (14), we put $P_{ij}(t_s)$ and $P'_{ij}(t_s)$, the minimum value of the performance curve in the calculation of travel time. That means if there's no reinforcement, the capacity will drop to the lowest due to the disaster. But if there is a reinforcement, the performance of the tunnel is better, and the capacity of the tunnel will drop less than no reinforced.

$$min \sum_{ij} x_{ij}\, t_{ij}(x_{ij}) \tag{12}$$

$$x_{ij} = \sum_{k} f_k \lambda_{ijk} \tag{13}$$

$$t_{ij} = t_{0ij}\left(1 + 0.15\left(\frac{x_{ij}}{c_{ij} z_{ij} P'_{ij}(t_s) + (1 - z_{ij}) P_{ij}(t_s) c_{ij}}\right)^4\right) \tag{14}$$

$$\sum_{k} f_k = d_w \tag{15}$$

$$f_k \geq 0 \tag{16}$$

4. NUMERICAL EXPERIMENT

A case study is made over network in Nguyen-Dupuis (1984). There are 2 O-D pairs, 13 nodes, and 19 links in the network. We assume that there are 6 tunnels in this network. The links associated with tunnels are marked in red in Figure. 4.

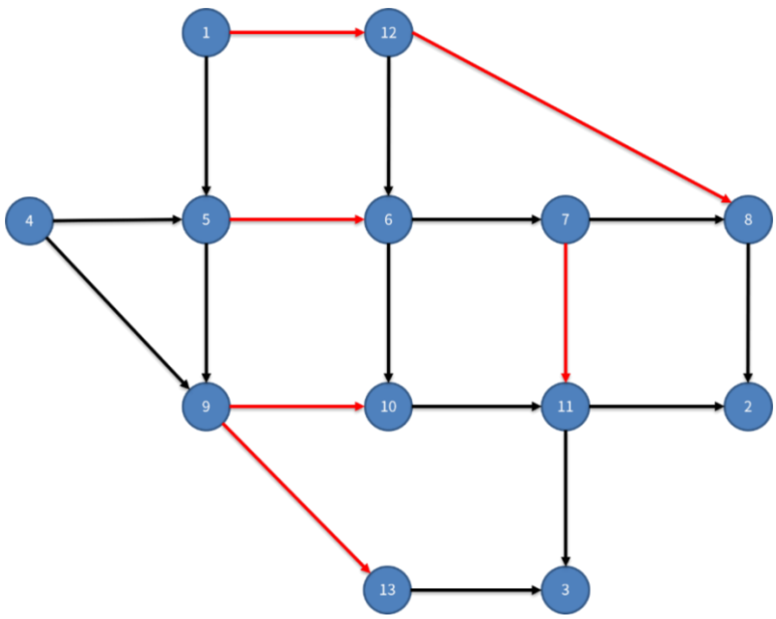

Figure 4. Nguyen-Dupuis network (1984)

The capacity and free-flow travel time are referred to Xu et al. (2015) and shown below in Table 4.

Table 4. Link characteristics of the Nguyen-Dupuis network (Xu, et al., 2015)

link_id	init_node	term_node	capacity	Free-flow travel_time
1	1	5	800	7
2	1	12	400	9
3	4	5	200	9
4	4	9	800	5
5	5	6	350	3
6	5	9	400	9
7	6	7	800	4
8	6	10	250	13
9	7	8	250	5
10	7	11	300	9
11	8	2	550	7
12	9	10	550	10
13	9	13	600	9
14	10	11	700	6
15	11	2	500	8
16	11	3	300	8
17	12	6	200	7
18	12	8	400	5
19	13	3	600	11

After the minimum cut problem, tunnels on links (9,10), (5,6), (13,3) and (1,12) are identified as the four bottleneck tunnels that are suggested being reinforced first. We assume that the government only have the resources to reinforce one tunnel in the first case (b=1). The bi-level model is employed to find the most critical tunnel to reinforce. The optimal reinforcement strategy is to reinforce the tunnel on (9,10), and total resilience increase from 38.7315 to 39.5014. The result shows that the network with reinforcement can have a better performance than no reinforcement (b=0). Since that the reinforcement is implemented to ensure better performance curve of the link (tunnel). The tunnel is more likely to work with higher performance (capacity) after being impacted.

Table 5. Results in different budget limits

	Tunnel (1,12)	Tunnel (5,6)	Tunnel (9,10)	Tunnel (13,3)	Resilience
$b = 0$	X	X	X	X	38.7315
$b = 1$	X	X	O	X	39.5014
$b = 2$	X	X	O	O	39.5014
$b = 3$	X	O	O	O	39.5014
$b = 4$	O	O	O	O	39.5014

The network resilience under different budget limits are shown in Table 5. It can be seen that with the higher budget limit, there are more tunnels that can be reinforced. But to the network, it's not always helps increase the network resilience. It is because the resilience is calculated in series and parallel parts. Since the tunnels are in series, reinforcing a tunnel that does not have the worst performance curve cannot improve resilience. This is because, in a series system, the overall resilience is determined by the tunnel with the lowest performance curve.

5. CONCLUDING REMARKS

The model proposed in this study is able to determine tunnel reinforcement strategies that can effectively optimize network resilience in pre-disaster planning, as demonstrated in the provided case study in comparison with no reinforcement situation. This implicates that the network is more robust to disaster impact and can continue better performance by employing the determined reinforcement strategies. Based on the preliminary results of this study to factor traffic flow distribution in roadway network resilience optimization, some directions for future work to test and enhance the proposed bi-level model are listed below:

1) A case study needs to be further extended to a real-world network to ensure the practicability of the developed model.
2) The performance curves in more complicated form or capturing more details about the disaster impact and recovery process need to be considered in the model to better reflect the realism of disaster management practice.
3) More sophisticated consideration of reinforcement strategies (for example, different level of strengthening) and spatial relationships between tunnels in the network needs to be further explored for in-depth insights for infrastructure management from a network modeling perspective.

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