

Multi-disruption resilience assessment of rail transit systems with optimized commuter flows

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Abstract

This paper studies the resilient performance of urban rail transit systems by extending a linear programming optimization model, which can provide optimized commuter flows with contingency routing under multiple disruptions. The rail transit systems in Singapore and Chongqing (China) are selected as case studies, and the system resilience and the effectiveness of providing bus-bridging services are comparatively studied. Intuitively, failures of the interchange stations would inevitably lead to a significant loss of resilience due to deteriorated network connectivity. However, the Singapore case shows that attacking those interchange stations does not always result in an extensive resilience loss. Comparing with the Chongqing case, it is discernible that the position of interchange stations would affect the system resilience. The numerical simulations reveal that the positive effect of providing bus-bridging strategy, in terms of improving the system resilience, is heterogeneous in different systems, which varies from 14% to 30% on average. As demonstrated in the sensitivity on travel demands, this positive effect is robust, yet dynamic, indicating that there is no one-size-fits-all solution for designing transfer-based recovery strategies in disruption management of rail transit systems. The managerial implications for decision makers are also provided and discussed in terms of infrastructure planning.

Keywords: Resilience; Rail transit systems; Bus-bridging services; Strategic recovery; Linear programming model

1. Introduction

The urban built environment is facing an increasing number of various disruptions, ranging from natural hazards and disasters such as earthquakes, extreme weather events (Chen & Wang, 2019), and rising sea levels in coastal cities, to man-made stresses and deliberate vandalisms such as severe congestion and terrorist attacks (Godschalk, 2003). For the year 2020, we all have witnessed that the on-going global COVID-19

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crisis can profoundly impact the way people travel and how cities are running (Batty, 2020). From an urban mobility perspective, making urban transportation infrastructure more resilient and robust against those disruptions has become a prominent and prioritized agenda in many cities in the world. Resilience is playing a key role in building smart and sustainable urban infrastructure (Sciamarelli, 2017). Not least because the introduction of this concept may provide promising solutions to ever-complex infrastructure protection problems but as much because the fast-developing information and data technologies can enable us to understand more about this emerging system concept. In this vein, we are in urgent demand of a practical strategy of building and understanding resilience to prevent those external shocks and suchlike disruptions in urban transportation systems and improve the adaptability and sustainability thereof. 10

Among the urban transportation systems, rail transit systems are of prevailing importance and value in terms of reducing emissions and lessening congestion. As a critical transportation infrastructure running seamlessly in a high frequency on a daily basis, monitoring its performance has always been a focus for the operators and managers (Jespersen-Groth et al., 2009). Even though many previous studies have been dedicated to investigating the urban rail transit systems, there are still needs for (1) a comparative study to quantitatively assess their operational resilience with various commuter attributes under multiple disruptions, and (2) a quantification and benchmark for exploring how effective the bus-bridging strategy could be in terms of improving overall system resilience. 15 20

To address the aforementioned needs, we further develop and extend the linear commuter contingency routing model proposed by Xu & Ng (2020). This model is a decent new model and can emulate the minute-by-minute commuter movement in a disruptive rail transit system, yet has some limitations. In this paper, we improve it and also differentiate from a three-fold perspective: (1) we further develop and extend it by explicitly taking into account the commuter transfer walking time between different platforms. In real-world rail systems, for example, Shanghai Metro, the walking time to transfer from Line 1 to Line 10 can take at least seven minutes. Under an emergency setting, it is cogent to capture the precise travel time required for re-routing; (2) we further innovatively justify the objective function, disruption system load, in a new perspective for the model and derive novel key insights mathematically (see Section 3.3). We show that minimizing the disruption system load at the final time period of the study horizon is equivalent to maximizing commuter outflows. In other words, we claim that maximizing outflows can be regarded as a special case of the disruption system load when only the load in the final time is of concern. In Xu & Ng (2020), these key observations were not examined. The observation is important in that the performance of outflows is a fairly common objective in optimizing routes in network flows (Dunn et al., 1994; Krozel et al., 2007), and thus, examining the connection of the disruption system load model with the common outflow maximization problem can deliver the generality of the model, which was not examined by Xu & Ng (2020) 25 30 35

either; (3) the developed model embeds high flexibility to evaluate multiple and different types of disruptions and scenarios, and this is a very important improvement of our work compared with what proposed by Xu & Ng (2020). 40

In this paper, we define system resilience using the classic time-series performance loss, which depicts the changes in the overall system serviceability. Random disruptions and malicious attacks are considered. Essentially, the random disruptions mimic the extensive aging process of the rail infrastructure, whereas the malicious attacks simulate the deliberate man-made threats. Two recovery strategies for depicting the capability of integrating external resources are adopted, including (1) a platform recovery sequence strategy based on network topology, and (2) providing arbitrary and deliberate bus-bridging transfers. Pooling bus-bridging services to disrupted rail stations can be a good representation of deliberately adding transfers, and thus creating connectivity to bridge the missing links (Pender et al., 2014; Diab et al., 2018). Even though these two types of strategy are widely studied in literature and applied in practice, the comparison 45 50 between these two within a resilience context are relatively less developed. In total, eight different combinations of attack-recovery strategies are simulated as standard tests, and their diverse system-level effects are investigated in a comparative analysis using Singapore and Chongqing case studies. The major innovative contributions of this paper can be summarized as follows:

- This study further extends a commuter contingency routing model by taking into account the commuter transfer walking time and justifies the objective function in a new perspective for the optimization problem, which improves the applicability of the model and also enriches the overall resilience assessment toolbox. 55
- Key practical insights from this new model are derived by mathematical formulations and the systemic resilience under multiple disruptions is evaluated, which helps to better understand the characteristics of resilient behaviors of urban transit systems in complex multi-disruption scenarios. 60
- This paper comparatively studies the resilience of urban rail transit systems and quantitatively explores the strength of providing bus-bridging transfer services in terms of improving system resilience. This fills a knowledge gap in the research of disruption management in rail transit studies.
- The investigation extrapolates intriguing managerial implications regarding metro layout planning and bus-bridging strategy design, which can be used as useful new evidence for multiple stakeholders and decision makers. 65

The remainder of this paper is organized as follows: Section 2 reviews the state-of-the-art knowledge on three resilience-related topics (disruption management, resilience quantification, and bus-bridging strategy

and services) and reiterates the knowledge gaps and missing links. Section 3 describes the methodology developed in this study. Section 4 introduces the network data and the initial settings for the simulations of the case studies. Section 5 presents the results of the numerical simulations and the sensitivity tests with demand variations. Section 6 discusses the potential managerial implications and limitations of this study. Finally, Section 7 concludes the paper and outlines the future work plan.

2. Literature review

2.1. Disruption management in rail transit systems

Urban rail transit systems are prone to a variety of risks and disruptions, and therefore, disruption management is one of the major research streams in the literature. In this stream, concepts such as system vulnerability, optimization of timetables, and rolling stock rescheduling play central roles (Narayanaswami & Rangaraj, 2013), and one of the effective approaches often found is to combine operation research and complex network science (Dekker et al., 2018). For years, scholars have been endeavored to develop fine models with high fidelity to investigate the operational characteristics of the systems. For example, Szymula & Bešinović (2020) proposed a novel passenger-centered Railway Network Vulnerability Model (RNVM) framework by finding the critical combination of links that cause the worst scenarios to passengers and trains. The study found that the critical links are highly dynamic instead of being static and fixed. Cacchiani et al. (2012) described a two-stage optimization model for determining robust rolling stock circulations for passenger trains. Cadarso et al. (2013) developed a two-step optimization model that combines the optimization of timetable and rolling stock schedules and a model for passenger’s travel behavior, which showed consideration to changing demand patterns. In addition, a few studies also addressed rolling stock rescheduling problems with consideration of uncertainties (van der Hurk et al., 2018) and passenger-centered approaches (Veelenturf et al., 2017) in rail disruption management.

Some recovery strategies considering various factors have also been discussed, such as real-time management, skip-stop strategy, roles of organizations, optimal resource allocation, and other overlooked factors that might reveal new insights for rail disruption management. For instance, Nielsen et al. (2012) dealt with the real-time disruption management of rolling stocks and provided decision-making support for a real-time disruption scenario. However, the demand changes caused by the re-routing of passengers were not considered in this study. In addition, the operational resilience of the system under multiple disruptions was not taken into account either. Gao et al. (2016) studied the reschedule problem of a metro line after disruptions with a proposed optimization model. The study found that if the skip-stop strategy is properly adjusted during the recovery stage, the total waiting time of passengers could be significantly reduced. Jespersen-

Groth et al. (2009) discussed the process of disruption management and the different roles that various organizations play during this management process in railway transportation. Jin et al. (2015) introduced a game-theory-based application of optimal resource allocation problems in urban rail transit systems by deploying protective resources against intentional attacks. Sun & Guan (2016) studied the vulnerability of the Shanghai metro network, considering several unexplored factors such as passenger betweenness centrality, number of missed trips, weighted average path length, and weighted global efficiency. They showed that the lines carrying more passengers generally have a larger impact on the network vulnerability. Huang et al. (2020) proposed a Bayesian network model to predict three main negative effects of disruptions during train operations including primary delay, the number of affected trains, and total system delay.

2.2. Resilience quantification and assessment in rail transit systems

The resilience and vulnerability analysis on general transportation networks, especially road networks, have been extensively studied (Mattsson & Jenelius, 2015; Faturechi & Miller-Hooks, 2015; Gu et al., 2020). In the studies focusing on rail transit systems, resilience has been largely investigated with an emphasis on network topologies and operational measures (Lu, 2018). In the first cohort, network centrality measures and connectivity methods are frequently employed (Derrible & Kennedy, 2010; Zhang et al., 2015; Dimitrov & Ceder, 2016; López et al., 2017). In the meantime, scholars have also been developing novel resilience indexes and metrics to define and describe system resilience (Chen & Miller-Hooks, 2012). In addition to system behaviors, some have sought to consider more aspects, such as user experience and system-of-systems viewpoint. Vodopivec & Miller-Hooks (2019) quantified the resilience of transit systems from a perspective of user resilience and their experience and developed a multi-valued dependency graph framework with a focus on diverse populations of passengers. Adjetey-Bahun et al. (2016) developed a simulation-based model that considers all subsystems of the mass railways systems, including transportation, power, telecommunication, and organization subsystems, and showed that capacities such as absorption, adaptation, and recovery can indeed enhance system resilience. Khadilkar (2017) evaluated the resilience (in terms of robustness) with the operational delays in a railway network by proposing a stochastic delay propagation model for delay identification at both primary and secondary levels. Readers can also refer to other detailed review papers for a further comprehensive understanding of the resilience assessment problem in rail transit systems and other transport systems, such as Bešinović (2020), Pender et al. (2012), Mattsson & Jenelius (2015), and Wan et al. (2018).

2.3. Bus-bridging strategy and service

The bus-bridging service, or the rail replacement bus, is not uncommon in the practical day-to-day management of rail transit systems (Pender et al., 2013; Jin et al., 2016), and it has been well-documented and

studied in the literature as well. For instance, Codina et al. (2013) proposed a mathematical programming model and a heuristically derived solution for planning the services of a set of auxiliary bus lines. The work specifically considered the congestion conditions. Nonetheless, the scope was on the management and design of the bus services rather than the resilience of the rail transit system. Jin et al. (2014) introduced a localized integration with bus services for enhancing the rail transit network resilience, which is achieved by increasing the capacity of bus services that run in parallel with affected rail lines as well as those connecting different rail lines. Diab et al. (2018) explored different aspects and impacts of providing bus-bridging services in response to service interruptions of the subways and streetcars in Toronto. The work investigated the size of the deployment and the system response and recovery times using detailed report data, and empirically found that dynamic fluctuations can be observed not only in the number of bus services over time but on the service response and recovery times as well. Some have studied, in detail, the design of bus-bridging services, which incorporates bridging routes, frequency, service flexibility, and initiation time (Zhang & Lo, 2018). To name a few, Gu et al. (2018) proposed a two-stage model to optimize the bridging plans and the assignments to buses with a balanced objective of operational priorities by minimizing bridging time and passenger delay. Luo & Xu (2021) also developed a two-stage model for bus bridging services, which were considered in an integrated network involving not only buses that were specialized for bridging purposes, but also existing operation-as-usual buses and remaining railway capacities after disruptions. Their framework was proposed mainly to address the challenge arising from demand and capacity stochasticity. Hu et al. (2016) presented a nonlinear integer programming model to plan the bus bridging as an evacuation measure along a rail transit line. De-Los-Santos et al. (2012) provided a rail network robustness measure from the perspective of users and compared system behaviors under disruptions with and without bus bridging services.

2.4. Research gaps

From the above review, it is clear that those studies have significantly contributed to how we might effectively depict and capture the resilient performance and the operational characteristics of rail transit systems. However, there are two main research gaps that can be summarized: (1) studies about quantitatively comparing resilience and its characteristics under multiple disruptions in different rail transit systems have been less developed; (2) there is still a lack of evidence on how much bus-bridging service can improve the system resilience, and the heterogeneity of its effectiveness still needs to be quantitatively explored and benchmarked in rail transit studies. As stated in the previous section, we will address these two research gaps in this paper.

3. Methodology

In this section, we introduce the proposed analytical framework, the commuter movement model, the simulation of disruption-recovery scenarios, and the metric for quantifying system resilience.

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3.1. Analytical framework

The proposed methodological framework in this paper is illustrated in Figure 1. Initially, commuters follow a pre-defined path moving from their origins to destinations under normal conditions (i.e., without disruption). When a platform is disrupted and corresponding trains are affected, commuters will have to alter their travel trajectory. A linear optimization model extended from Xu & Ng (2020) is developed to capture such trajectory change under disruptions. This model evaluates the total queue, commuter outflows, and disruption system load. The outputs of this model serve as time-series inputs of the next step - evaluation of different recovery strategies. After that, for evaluating the system resilience under those different scenarios, a time-series resilience metric based on performance loss is selected and implemented. Finally, we obtain the resilience curves and quantify resilience for all simulated scenarios in all case studies to comparatively study the resilience performance and system-level characteristics.

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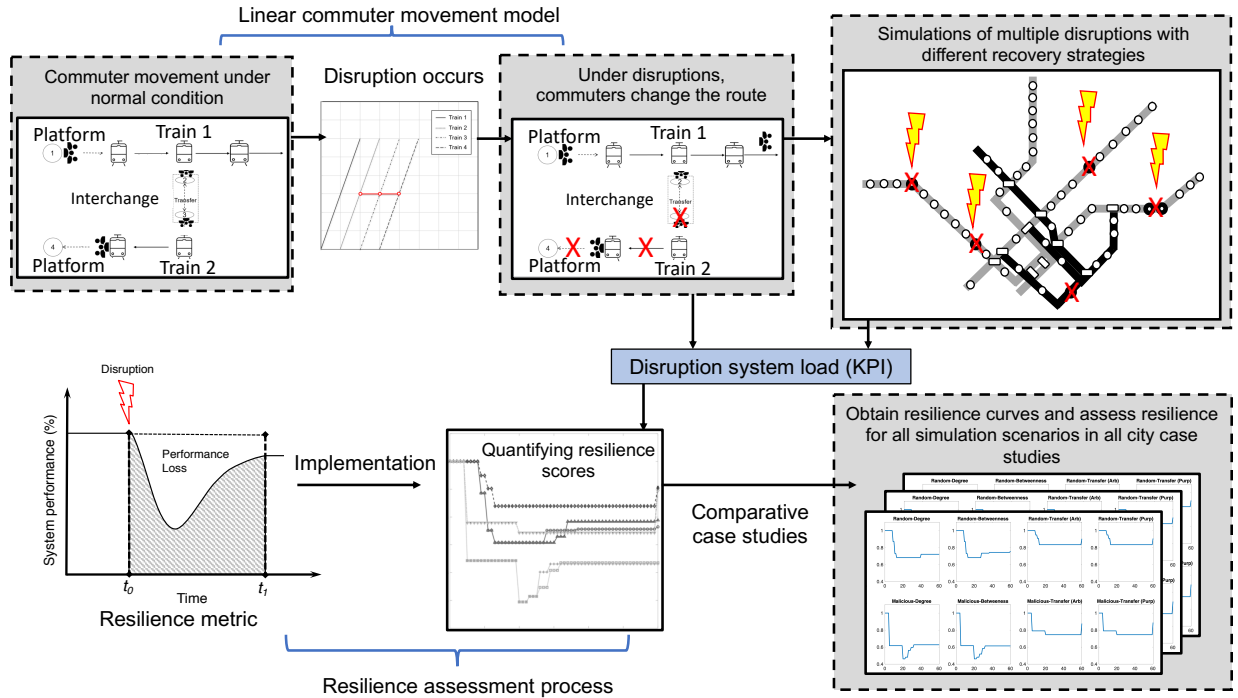


Figure 1: The proposed methodological framework in this study (please note that all inner figures are for illustration only).

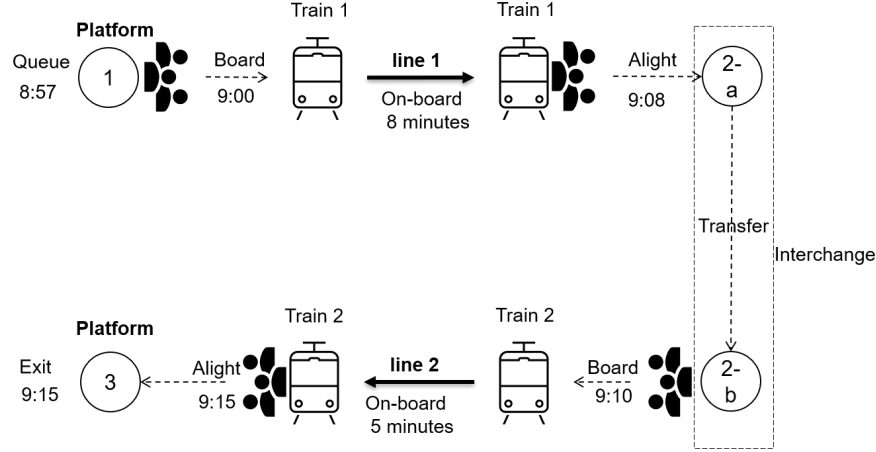


Figure 2: An illustrative example of the commuter movement in a rail transit network.

3.2. Linear commuter movement model under platform and train disruptions

The commuter flow logic, which involves commuters' movements at platforms and in trains in a rail transit network, can be illustrated by an example shown in Figure 2. In this example, commuters queue at platform 1 at 8:57, waiting for train services on line 1. These commuters board a train 3 mins later. Another 8 mins later they alight at interchange platform 2-a, and transfer to platform 2-b. At 9:10, they board train services on line 2. Finally, commuters arrive at their destination platform 3 and exit at 9:15.

We represent the rail transit network by a directed graph $\mathcal{G} = (\mathcal{N}, \mathcal{A})$ where $\mathcal{N}$ is the set of all platforms and $\mathcal{A}$ is the set of all directed links. Throughout this paper, we differentiate the term *platform* from the *station*. Specifically, a *platform* is where commuters queue and board train services, and a *station* consists of one (if it is a non-interchange station) or more (if it is an interchange) such platforms. We also emphasize that the disruption events occur at the platform level. A link is distinguished as a *rail link* where trains run and a *foot link* where commuters walk on foot to make transfers.

Let Ω denote the set of all Origin-Destination (OD) pairs of commuters, indexed by ω , with origin $s(\omega)$ and destination $e(\omega)$. Let $\mathcal{T} = \{k, \dots, T\}$ be the set of time periods considered in this study, in which $1 \leq k < T$ denotes disruption commencement time. Let $\mathcal{V} = \{1, \dots, V\}$ denote the set of train services in the time horizon. To capture commuter movement logic, decision variables are defined as follows: $q_{j,t}^\omega$ denotes commuter flows with OD pair ω queueing at platform j at time t ($q_{j,t}^\omega$ is set to equal 0 if $j = e(\omega)$); $b_{v,t,j}^\omega$ denotes commuter flows with OD pair ω boarding train v at platform j at time t ($b_{v,t,j}^\omega$ is set to equal 0 if $j = e(\omega)$); $l_{v,t}^\omega$ denotes commuter flows with OD pair ω on-board in train v at time t ; $d_{i,j,t}^\omega$ denotes commuter flows with OD pair ω walking on foot link $(i, j) \in \mathcal{A}_{foot}$ at time t ; $a_{v,t,j}^\omega$ denotes commuter flows with OD pair ω alighting from train v at platform j at time t ($a_{v,t,j}^\omega$ is set to equal 0 if $j = s(\omega)$); $o_{j,t}^\omega$

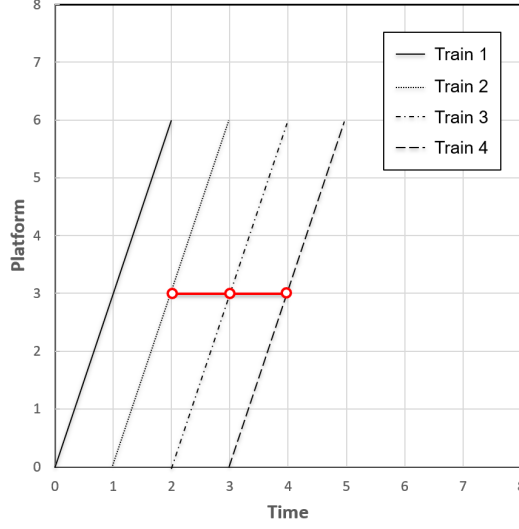


Figure 3: Illustration of platform disruption and its impact on the status of trains following different schedules.

denotes commuter flows with OD pair ω exiting at platform j at time t ($o_{j,t}^\omega$ is set to equal 0 if $j \neq e(\omega)$). Furthermore, let parameter $D_{j,t}^\omega$ denote the commuter demand for OD ω originating from $s(\omega) = j$ at time t , by definition, $D_{j,t}^\omega = 0$, $j \neq s(\omega)$. Notation introduced in this paper is listed in Table 1.

Table 1: Summary of notations in methodology.

$\mathcal{N}$	set of nodes representing rail platforms
$\mathcal{A}_{foot}$	set of foot links where commuters can walk and transfer
Ω	set of Origin-Destination (OD) pairs, indexed by ω , with origin platform $s(\omega)$, destination platform $e(\omega)$
k	disruption commencement time
$\mathcal{T}$	set of time periods considered, $\mathcal{T} := \{k, \dots, T\}$, i.e., starting from disruption commencement time k to time T
$\mathcal{V}$	set of train runs during study time, indexed by v
$D_{j,t}^\omega$	commuter demands for OD ω originating from platform j at time $t \geq k$, $D_{j,t}^\omega = 0$ if $j \neq s(\omega)$ by definition
C_v	capacity of train run v
$I_{v,t,j}$	binary train timetable representation, 1 if train run v calls at platform j at time t , 0 otherwise
$\sigma_{i,j}$	commuter transfer time by foot link between platform i and platform j
$\theta_{v,t}$	binary parameter, taking value of 1 if train service v is disrupted at time t , and 0 otherwise
$\lambda_{j,k}$	binary parameter, taking value of 1 if platform j is disrupted at disruption commencement time k , and 0 otherwise
τ	platform disruption duration
$q_{j,t}^\omega$	commuter flows with OD pair ω queueing at platform j at time t , $q_{j,t}^\omega = 0$ if $j = e(\omega)$
$b_{v,t,j}^\omega$	commuter flows with OD pair ω boarding train v at platform j at time t , $b_{v,t,j}^\omega = 0$ if $j = e(\omega)$
$l_{v,t}^\omega$	commuter flows with OD pair ω on-board in train v at time t
$d_{i,j,t}^\omega$	commuter flows with OD pair ω walking on foot link $(i,j) \in \mathcal{A}_{foot}$ at time t
$a_{v,t,j}^\omega$	commuter flows with OD pair ω alighting from train v at platform j at time t , $a_{v,t,j}^\omega = 0$ if $j = s(\omega)$
$o_{j,t}^\omega$	commuter flows with OD pair ω exiting at platform j at time t , $o_{j,t}^\omega = 0$ if $j \neq e(\omega)$.

It is assumed that all trains running across disrupted platforms during downtime would be canceled. The logic of how a train can be affected by a disrupted platform is illustrated by an example shown in Figure 3. In this example, four trains are dispatched to a line running through platforms 0 to 6, with a headway of 1 unit of time. Platform 3 is disrupted at time 2, and the disruption lasts for 2 time units. In this case, train 1 is not affected because disruption has not yet started at the time it runs across platform 3. However, train 2,

train 3, and train 4 are all affected since they respectively run over platform 3 at the beginning, during, and at the end of this particular disruption event. From this illustration, it is straightforward to see that a train service would be affected if it is calling at one disrupted platform (at least), and not affected otherwise. To formalize this description, let parameter $I_{v,t,j}$ denote the train timetable, with $I_{v,t,j} = 1$ if train v stops at platform j at time t , and $I_{v,t,j} = 0$ otherwise. Let binary parameter $\lambda_{j,k}$ represent the status of platforms, 210 taking the value of 1 if platform j is disrupted at time k , 0 otherwise. Let binary parameter $\theta_{v,t}$ represent the status of train services, taking the value of 1 if train service v is canceled at time t due to platform disruptions at disruption time k , 0 otherwise. Let τ represent the platform downtime. By logic, we have:

$$\theta_{v,t} = \begin{cases} 0, & \text{if } \sum_{j \in \mathcal{N}} (\lambda_{j,k} \sum_{k \leq t' \leq \min\{t, k+\tau\}} I_{v,t',j}) = 0 \\ 1, & \text{if } \sum_{j \in \mathcal{N}} (\lambda_{j,k} \sum_{k \leq t' \leq \min\{t, k+\tau\}} I_{v,t',j}) > 0 \end{cases} \quad \forall v \in \mathcal{V}, t \in \mathcal{T} : t \geq k \quad (1)$$

From (1), if every term $\lambda_{j,k} \sum_{k \leq t' \leq \min\{t, k+\tau\}} I_{v,t',j}$ is 0, we have train service v is operational (i.e., not affected) at time t . For each term, this is true if either v does not call at j during the time interval $[k, t]$ 215 if $t \leq k + \tau$, or if it does not call at j over the entire disruption interval $[k, k + \tau]$ if $t > k + \tau$ (i.e., $I_{v,t',j} = 0, \forall t' \in [k, \min\{t, k + \tau\}]$), or if platform j is not disrupted. If any such conditions do not hold, train v is not available at time t .

Given the aforementioned definitions, the commuter movement model was revisited and extended as

follows:

$$\min \left(\sum_{\omega \in \Omega} \sum_{j \in \mathcal{N}} \sum_{t \in \mathcal{T}: t \geq k} q_{j,t}^{\omega} + \sum_{\omega \in \Omega} \sum_{v \in \mathcal{V}} \sum_{t \in \mathcal{T}: t \geq k} l_{v,t}^{\omega} \right) / (T - k) \quad (2)$$

$$\begin{aligned} \text{s.t. } q_{j,t}^{\omega} = & q_{j,t-1}^{\omega} + D_{j,t}^{\omega} + \sum_{i: (i,j) \in \mathcal{A}_{foot}, t': t' + \sigma_{i,j} = t} d_{i,j,t'}^{\omega} - \sum_{i: (j,i) \in \mathcal{A}_{foot}} d_{j,i,t}^{\omega} \\ & + \sum_{v \in \mathcal{V}} a_{v,t,j}^{\omega} - \sum_{v \in \mathcal{V}} b_{v,t,j}^{\omega} - o_{j,t}^{\omega}, \quad \forall \omega \in \Omega, j \in \mathcal{N}, t \in \mathcal{T}: t \geq k \end{aligned} \quad (3)$$

$$l_{v,t}^{\omega} = l_{v,t-1}^{\omega} + \sum_{j \in \mathcal{N}} b_{v,t,j}^{\omega} - \sum_{j \in \mathcal{N}} a_{v,t,j}^{\omega}, \quad \forall \omega \in \Omega, v \in \mathcal{V}, t \in \mathcal{T}: t \geq k \quad (4)$$

$$\sum_{\omega \in \Omega} l_{v,t}^{\omega} \leq C_v(1 - \theta_{v,t}), \quad \forall v \in \mathcal{V}, t \in \mathcal{T}: t \geq k \quad (5)$$

$$a_{v,t,j}^{\omega} \leq I_{v,t,j} \sum_{t' \leq t} D_{s(\omega),t'}^{\omega}, \quad \forall \omega \in \Omega, v \in \mathcal{V}, j \in \mathcal{N}, t \in \mathcal{T}: t \geq k \quad (6)$$

$$b_{v,t,j}^{\omega} \leq I_{v,t,j} \sum_{t' \leq t} D_{s(\omega),t'}^{\omega}, \quad \forall \omega \in \Omega, v \in \mathcal{V}, j \in \mathcal{N}, t \in \mathcal{T}: t \geq k \quad (7)$$

$$o_{j,t}^{\omega} = 0, \quad \forall \omega \in \Omega, j \in \mathcal{N}, t \in \mathcal{T}: t \geq k \& j \neq e(\omega) \quad (8)$$

$$\mathbf{q}, \mathbf{l}, \mathbf{a}, \mathbf{b}, \mathbf{d}, \mathbf{o} \geq \mathbf{0} \quad (9)$$

The objective in (2), defined as the *disruption system load*, minimizes the average commuter flows detain-
ing in the rail transit system since disruption commencement. At any given time t , the total commuter flows 220
in the system consists of those queueing at platforms $\mathbf{q}_t$, and those on-board in trains $\mathbf{l}_t$. Prior to disruptions,
the queueing flows are assumed to be $\bar{q}_{j,k-1}^{\omega}$, i.e., queueing flows of OD pair ω at platform j before disruption
commences (i.e., time $k-1$) and the on-board flows are assumed to be $\bar{l}_{v,k-1}^{\omega}$, i.e., train load flows of OD pair
 ω at train v before disruption commences. It is straightforward to see that maximizing commuter outflows
is equivalent to minimizing the disruption system load at the final time T , i.e., the corresponding parts in 225
(2) with $t = T$. In other words, maximizing outflows can be regarded as a special case of the disruption
system load (2) when only the load in the final time is of concern. This observation was missing in the
original model in Xu & Ng (2020). Constraints (3) describe the flow balance of commuters at each platform,
for each OD pair ω and time t . Basically, the constraints state that the number of commuters waiting at
the platform in the current period is accounted for by commuters queueing in the previous period, plus all 230
commuters arriving at the platform and minus commuters departing from the platform in the current pe-
riod. Commuters arriving at that particular platform include those whose origin is the platform, those who
make transfers on foot from another platform via a foot link to this platform, and those who alight at the
platform. Commuters departing from the platform include those who board a train at the platform, those

who transfer out via foot links, and those whose destination is this platform. In this balance constraint, we newly introduce the transfer time, $\sigma_{i,j}$, which was not considered in Xu & Ng (2020) either. $\sigma_{i,j}$ represents the walking time between platform i and j on foot. The walking time can be seen as the transfer-related cost for commuters. The introduction of this notation extends the model in the way that too-many-transfer-route can be avoided. Constraints (4) describe that the flow balance of commuters onboard, for each OD pair ω at time t , determined by on-board commuters in the earlier period plus those boarding the train and minus those alighting from it. Constraints (5) impose available capacity limit given train status. Constraints (6) ensure that commuters can only alight from a train v at a platform j at time t only if v calls at j during t according to the timetable. Similarly, Constraint (7) says that commuters on a platform can only board a train at the time the train calls at the platform. Constraint (8) impose that the outflow is zero if not at the destination platform. And (9) impose decision variable domains.

3.3. Justification of disruption system load model

We extend the feasibility of model (2)-(9) here for two more *novel* implications of the objective function defined in (2). It essentially accounts for the presence of every single commuter in the rail transit system (onboard or waiting at a platform) every time after the commencement of the disruption event. Hence, the longer the commuters dwell in the system, the more they contribute to the overall disruption system load.

In particular, we define the *flow time* of a commuter as the time from when this commuter enters the rail transit system (i.e., arrives at the origin platform), to the time when this commuter exits the system (i.e., reaches the destination platform). By this definition, the disruption system load defined in (2) is equivalent to the total flow time of commuters entering since the disruption and the remaining flow time of commuters entering before the disruption, assuming all commuters eventually reach their destination platforms after a disruption. Simply put, let ν denotes the index of a commuter, $\mathcal{D}$ denotes the set of all commuters, t_ν denotes the entry time of commuter ν , η_ν represents the flow time of commuter ν , and hence $t_\nu + \eta_\nu$ is the exit time of ν (at the destination platform). Define binary indicator $\mathbb{I}_\nu(t) = 1$ if $t_\nu \leq t \leq \eta_\nu + t_\nu - 1$, $\mathbb{I}_\nu(t) = 0$ otherwise. We then have:

$$\begin{aligned}
\frac{(\sum_{\omega \in \Omega} \sum_{j \in \mathcal{N}} \sum_{t \in \mathcal{T}: t \geq k} q_{j,t}^\omega + \sum_{\omega \in \Omega} \sum_{v \in \mathcal{V}} \sum_{t \in \mathcal{T}: t \geq k} l_{v,t}^\omega)}{T - k} &= \frac{\sum_{\nu \in \mathcal{D}} \left\{ \sum_{t \geq k} \mathbb{I}_\nu(t) \right\}}{T - k} \\
&= \frac{\sum_{\nu \in \mathcal{D}: t_\nu \geq k} \left\{ \sum_{t \geq k} \mathbb{I}_\nu(t) \right\} + \sum_{\nu \in \mathcal{D}: t_\nu < k} \left\{ \sum_{t \geq k} \mathbb{I}_\nu(t) \right\}}{T - k} \\
&= \frac{\sum_{\nu \in \mathcal{D}: t_\nu \geq k} \eta_\nu + \sum_{\nu \in \mathcal{D}: t_\nu < k} \{\eta_\nu + t_\nu - k\}}{T - k}
\end{aligned} \tag{10}$$

Here, in equations (10), the first equality follows directly from the definition of the disruption system load in (2), which accounts for all the commuters in the transit system after the disruption commencement time k until T . The second equality accounts for the commuters who enter after and before the disruption commencement time k respectively. The last equality shows that each commuter contributes to the objective function value, either a load level equivalent to the flow time or a *remaining flow time* for commuters who entered before the commencement of the disruption.

Hence, based on the assumption that commuters are eventually able to reach their destination platforms, minimizing the flow times of commuters is equivalent to minimizing the disruption system load, which is intuitively consistent since the only way to reduce the system load is to increase outflows. However, in the context of disruptions, minimizing flow times may not always be appropriate. For instance, if disruptions last for a very long duration (e.g. $(\eta_\nu + t_\nu) \leq T$ does not hold), or all rail transit routes to the destination platform are completely cut off, then flow times technically become arbitrarily large, and minimizing flow times is not meaningful. This, however, does not pose an issue for the disruption system load (2), since the presence of these commuters is simply accumulated into the next time period's levels of commuters who are waiting $\mathbf{q}_t$ and onboard $\mathbf{l}_t$ through the flow balance constraints (3) and (4). Hence, the objective function of minimizing disruption system load offers more generality and flexibility than minimizing flow times for our purpose in this study.

3.4. Simulations of attack, recovery and commuter demand scenarios

We consider random disruptions and malicious attacks, which are the two representative and standard types of disruptions in critical infrastructure systems (Ouyang et al., 2019; Goldbeck et al., 2019; Liu & Song, 2020). Random disruptions can mimic the extensive aging process of the rail infrastructure overtime in a changing environment, and malicious attacks reflect the increasingly frequent occurrence of intentional man-made disruptions such as deliberate vandalism. The following Table 2 shows the notations used for describing the simulation process as mentioned follows.

Table 2: Notation used for simulations

$u(j)$	degree of node j
$v(j)$	betweenness of node j
n_r	number of disrupted platforms under random disruptions, with set $\mathcal{N}_r = \{j_i \in \mathcal{N} : i = 1, \dots, n_r\}$
n_m	number of disrupted platforms under malicious attacks, , with set $\mathcal{N}_m = \{j_i \in \mathcal{N} : i = 1, \dots, n_m\}$
τ_r	time interval between the disruption of two subsequent disruptions under random disruptions
τ_s	time interval between the recovery of two subsequent disruptions given sequence-based recovery strategy

The disrupted platforms under random disruptions are selected by assuming independent and identical disruption probability for each platform. In other words, given N platforms, the probability of disrupting

each platform is $1/N$. The assumption of uniformly distributed disruption events in railway systems has been made in the literature (e.g., see Hong et al. (2015)). In the meantime, we remark that our approach can be easily generalized to consider other forms of disruption probabilities. Another important feature of random disruptions is that the failures of the selected platforms occur by following a sequence. Suppose now the set of the identified platforms is $\mathcal{N}_r = \{j_i \in \mathcal{N} : i = 1, \dots, n_r\}$, where n_r is the number of disruptions under random disruptions. Given the first disruption commencement time k , and the time interval (denoted by τ_r) for a subsequent platform disruption, the disruption of the selected platforms occurs, therefore, at $t = k, k + \tau_r, \dots, k + (n_r - 1)\tau_r$. Since time $t = k + (n_r - 1)\tau_r$, the disruption state of these platforms would last for another T_r time period, where we define T_r as the disruption duration of random disruptions.

The recovery time hence starts from $t = k + (n_r - 1)\tau_r + T_r + 1$. For system recovery, we consider two recovery strategies: (1) *topology-based recovery*, and (2) *transfer-based recovery*. The former refers to the recovery process of disrupted platforms in the sequence according to *degree centrality (degree)* or *betweenness centrality (betweenness)*. This is considered an intuitive and basic strategy when focusing on the full knowledge of the system topology and structure. Let $u(j)$ denote the degree of node j , and $v(j)$ represents the betweenness of node j . The recovery sequence of the platforms in $\mathcal{N}_r$ follows the descending order of $u(j)$ or $v(j)$. We assume that the time interval between recovering a platform and a subsequent platform is fixed, denoted by τ_s . Thus, the topology-based recovery (i.e., degree-based recovery or betweenness-based recovery) process spans from time $t = k + (n_r - 1)\tau_r + T_r + 1$ to time $t' = t + (n_r - 1)\tau_s$.

The latter, i.e., transfer-based recovery, refers to the process of recovering the disruption state of the rail transit network by adding bus-bridging services between rail platforms to improve the connectivity of the disrupted rail network. This widely applied mitigation strategy is the key testing point of this study. This strategy is further divided into *arbitrary (Arb)* and *purposefully (Purp)* transfers. The former is to add bus bridging links between two arbitrarily selected platforms which are not necessarily those disrupted ones. It is not uncommon to see bus-bridging service as a supplementary public service for railway systems. The latter is to provide bridging services explicitly between two disrupted platforms, which are specialized for recovering the suspended connectivity of the rail transit system, with reserved bus resources. The two types of bus-bridging transfers are demonstrated in Figure 4. The reason why we design the recovery strategies as such is to (1) quantitatively investigate the effectiveness of providing bus-bridging services and see how it influences the system resilience, and (2) compare the effectiveness of providing bridging buses in different approaches.

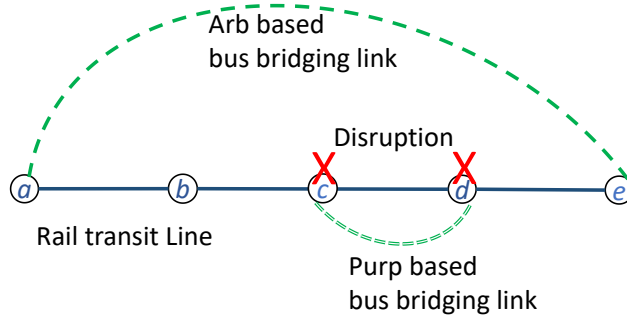


Figure 4: An illustrative example of arbitrary transfer-based bus-bridging link and purposely transfer-based bus-bridging link for a rail transit line where two platforms are under disruptions.

For achieving a fair comparison of different disruption scenarios, the designed recovery strategies are also implemented in the context of malicious attacks. Here, we focus on those interchange stations in a given rail transit system as they are the critical stations where several rail lines can be jeopardized simultaneously once disrupted. Formally, let $\mathcal{N}_m = \{j_i \in \mathcal{N} : u(j_i) > 1, i = 1, \dots, n_m\}$, where n_m is the number of disrupted platforms under malicious attacks. Different from the setting of random disruptions, the disruption of interchange stations under the malicious attacks occurs concurrently rather than one by one in sequence (to capture the massive effect of deliberately-designed simultaneous attacks as compared to random failures). In this way, we have a total of $2 \times 4 = 8$ scenarios for assessing system resilience. For a clear exposition, we hereinafter use a combination term “malicious-transfer strategies” to represent that the transfer-based strategies are implemented to recover from malicious attacks. Other combination terms that occur as follows referring to similar meanings.

To conduct the sensitivity analysis of commuter demand, we consider three levels of demand, namely “normal”, “low” and “high” respectively. The “normal” level simulates the commuting on a typical workday and can be reasonably estimated from historical data (e.g., Automatic Fare Collection Systems data in Singapore). The “low” level of demand is half of the normal demand, while the “high” level is double of it.

3.5. Resilience assessment metric

Performance-based resilience can be evaluated based on the profile of the system performance loss, known as the “resilience curve” (Figure 5). This profile depicts the time-series performance of system functionality and can be utilized for most of the critical infrastructure systems, including road transportation systems (Tang, 2019). One Key Performance Indicator (KPI) is often selected to indicate the system functionality performance. Given the actual functionality performance $AP(t)$ being maintained at a normal 100% level, without any disruptions before time t_0 , $NP(t)$ and $AP(t)$ are at the same level within this period. If an

unexpected disruption event occurs at t_0 , the actual performance $AP(t)$ would drop due to the consequent functionality lost. After that, the system recovers, and its $AP(t)$ would reach a new stabilized level at time t_1 (This new stabilized level could be the same as the pre-event level or lower than the pre-event level). This “failure-recovery” process is a typical resilience curve (Tang et al., 2019). In this study, the KPI is selected as the normalized disruption system load, which is derived from the ratio between the *original* disruption system load value at time period t when there is no disruption and the *actual* disruption system load value given a disruption event. Thus, the higher the ratio is, the less disrupted the rail transit network is. Finally, to quantify resilience from the curve, a widely applied metric proposed by Ouyang & Dueñas-Osorio (2012) is adopted because (1) this metric has a value range of $[0, 1]$, which is intuitive and easy to conduct cross-comparison, and (2) the metric features excellent effectiveness and simplicity for applications. The metric is defined as follows.

$$RI = \frac{\int_{t_0}^{t_1} AP(t)dt}{\int_{t_0}^{t_1} NP(t)dt} \quad (11)$$

where, t_1 is the observation period, $AP(t)$ is the actual performance level at time t , and $NP(t)$ is the normal or expected performance level at time t , which is usually at 100% or an ideal level.

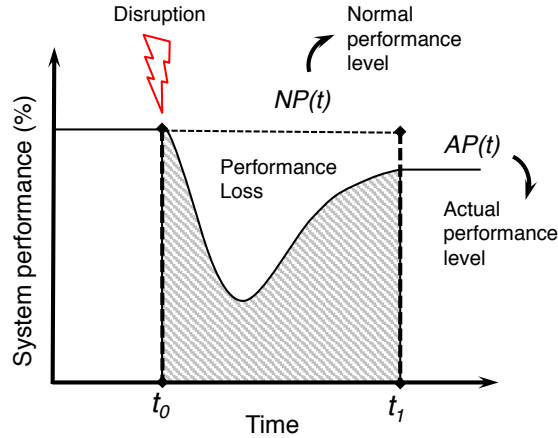


Figure 5: An illustrative example of the resilience curve paradigm. In this case, the post-event performance level is lower than the pre-event level. Modified based on Ouyang & Dueñas-Osorio (2012).

4. Network data description and settings

Singapore and Chongqing rail transit systems are selected in this paper as the case studies for the comparative analysis. The reason is two-fold: (1) The rail transit system of these two cities have distinct topological structures, whereby the system of Singapore case roughly has a radial morphology with concentrated interchange stations around the central area, while Chongqing case has a more distributed layout of

the interchange stations; (2) These two rail transit systems have a similar size in terms of platforms. We collected the network topology data using freely available online resources.

For the Singapore rail transit network (Figure 6), we consider North-South (NS) line, East-West (EW) line, North-East (NE) line, Downtown (DT) line, and Circle (CC) line, in which, a total of 77 platforms are included. The non-interchange stations (i.e., platforms) are represented by circles and the interchange stations (i.e., consisting of more than one platform) by rectangles. We consider 21502 commuters from 40 OD pairs entering continuously the network between 8:00 AM and 8:25 AM.

In terms of sampling disruption events, for random disruptions, we assume that the first platform disruption commences at 8:05 AM. After that, every two minutes a new arbitrary platform is disrupted. As a result, 6 platforms, Kallang (EW), Pasir Ris (EW), Bishan (NS), Bras Basah (CC), Hougang (NE), and Farrer Park (NE), are randomly disrupted by 8:15 AM, and the disruption lasts for another 10 mins. From 8:25 AM, recovery measures are taken place. For malicious attacks, we assume that all platform disruptions take place simultaneously from 8:05 AM, and the state continues until 8:20 AM. The disrupted platforms are all among the interchange stations, including platforms of City Hall (EW), Raffles Place (EW), Chinatown (NE), Dhoby Ghaut (NE), Dhoby Ghaut (NS), and Chinatown (DT). The disrupted platforms and their centrality measures are summarized in Table 3.

Table 3: Disrupted platforms of rail transit network in Singapore

Random disruptions				Malicious attacks			
Line	Platform Name	Degree	Betweenness	Line	Platform Name	Degree	Betweenness
EW10	Kallang	2	0.212	EW13	City Hall	3	0.195
EW1	Pasir Ris	1	0	EW14	Raffles Place	3	0.139
NS17	Bishan	2	0.101	NE4	Chinatown	3	0.219
CC2	Bras Basah	2	0.169	NE6	Dhoby Ghaut	4	0.304
NE14	Hougang	2	0.077	NS24	Dhoby Ghaut	4	0.217
NE8	Farrer Park	2	0.212	DT19	Chinatown	2	0.039

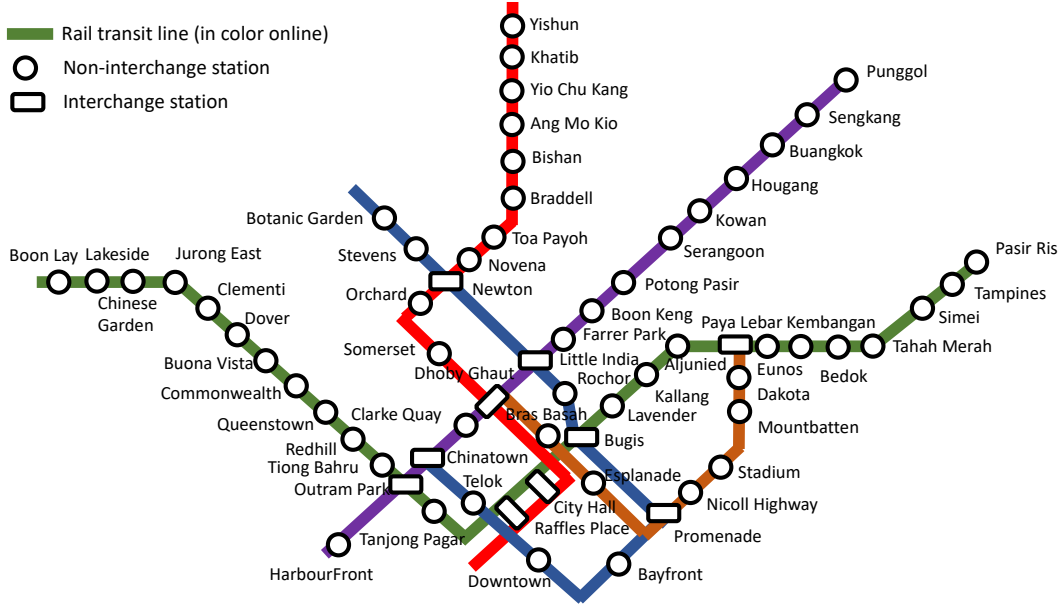


Figure 6: The simulated rail transit system in Singapore

In the case of Chongqing rail transit system (Figure 7), there are 76 platforms on five rail transit lines. We consider 22601 commuters from 40 OD pairs continuously entering the network between 8:00 AM and 8:25 AM. Similar to the Singapore case, 6 platforms including Lianglukou (Red), Gaomiao (Red), Majiayan (Red), Liziba (Green), Sigongli (Blue), and Lianhua Village (Yellow) are randomly disrupted by 8:15 AM and last for 10 mins. Failed platforms start to recover from 8:25 AM. For malicious attacks, the disrupted platforms are all among the interchange stations, including platforms of Xiaoshizi (Red), Jiaochangkou (Green), North Railway Station (Blue), South Railway Station (Yellow), Sigongli (Yellow), and Wulidian (Pink). The disrupted platforms and their centrality measures are summarized in Table 4.

Table 4: Disrupted platforms of rail transit network in Chongqing

Random disruptions				Malicious attacks			
Line	Platform Name	Degree	Betweenness	Line	Platform Name	Degree	Betweenness
1	Lianglukou	3	0.225	1	Xiaoshizi	2	0.127
1	Gaomiao Village	2	0.115	2	Jiaochangkou	2	0.043
1	Majiayan	2	0.105	3	North Railway Station	2	0.030
2	Liziba	2	0.048	Circle	North Railway Station	2	0.038
Circle	Sigongli	3	0.268	Circle	Sigongli	3	0.268
Circle	Lianhua Village	2	0.095	6	Wulidian	3	0.118

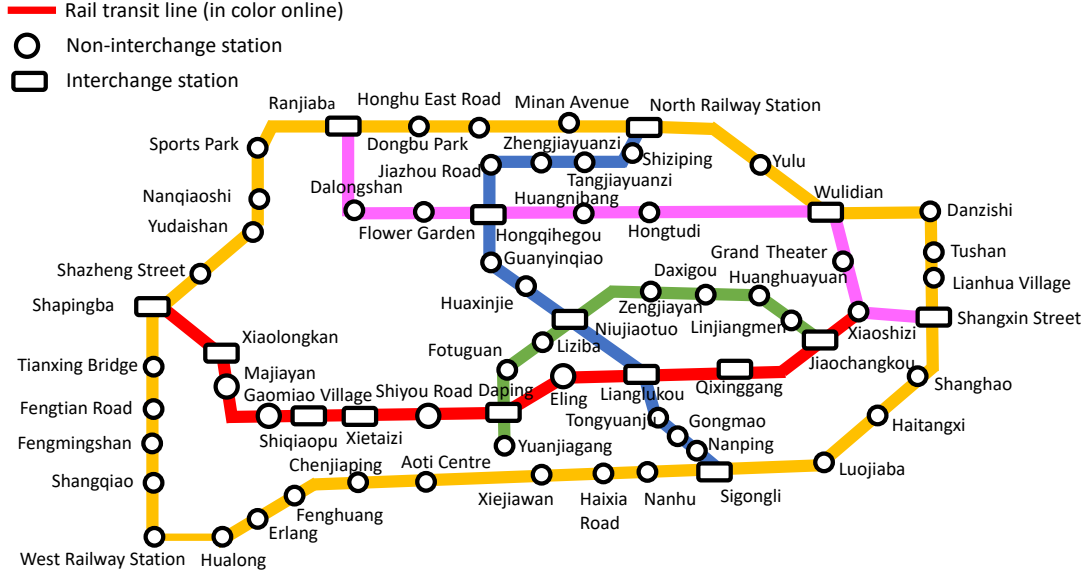


Figure 7: The simulated rail transit system in Chongqing

5. Results

5.1. Contingency routing after disruptions

The extended model (2)-(9) can allocate the best contingency route for commuters when multiple disruptions occur. Figure 8(a) illustrates the normal travel trajectory of commuters traveling between the origin platform, Outram Park (NE), and the destination platform, Bugis (DT), in the Singapore rail transit system. The trajectory is as follows: commuters first travel on NE line from the origin to the platform of Little India (NE), at which they transfer to the DT line and to the destination. Usually, commuters use mobile apps (e.g., Google Maps) to find such a travel route, which either has the shortest travel time or minimum transfers. However, given the disruption on the platform of Dhoby Ghaut (NE), this normal route is thus disabled. To respond to the disruption, the rail operator could activate the bus-bridging services connecting the two adjacent platforms of the disrupted platform (i.e., Clarke Quay (NE) and Little India (NE)) to recover the connection on NE line.

Alternatively, the model can also recommend contingency routes if bus-bridging services are not considered, as shown in Figure 8(b). Following the contingency route, commuters transfer to the CC line at Dhoby Ghaut (CC) and then detour through this line to transfer to Paya Labe (EW). After a third transfer from the EW line to the DT line, finally, they arrive at the destination platform of Bugis (DT). Compared to the normal route, commuters have to transfer more than twice to their destination. Even so, this detour is still reasonably acceptable under such emergency circumstances (Kunimatsu & Hirai, 2014) because the priority

is to reach the destination and exit from the rail transit system. However, this would inevitably increase the system load as commuters would stay longer in the transit system (including longer travel time and walking time during multiple transfers), and thus, affect the system functionality performance.

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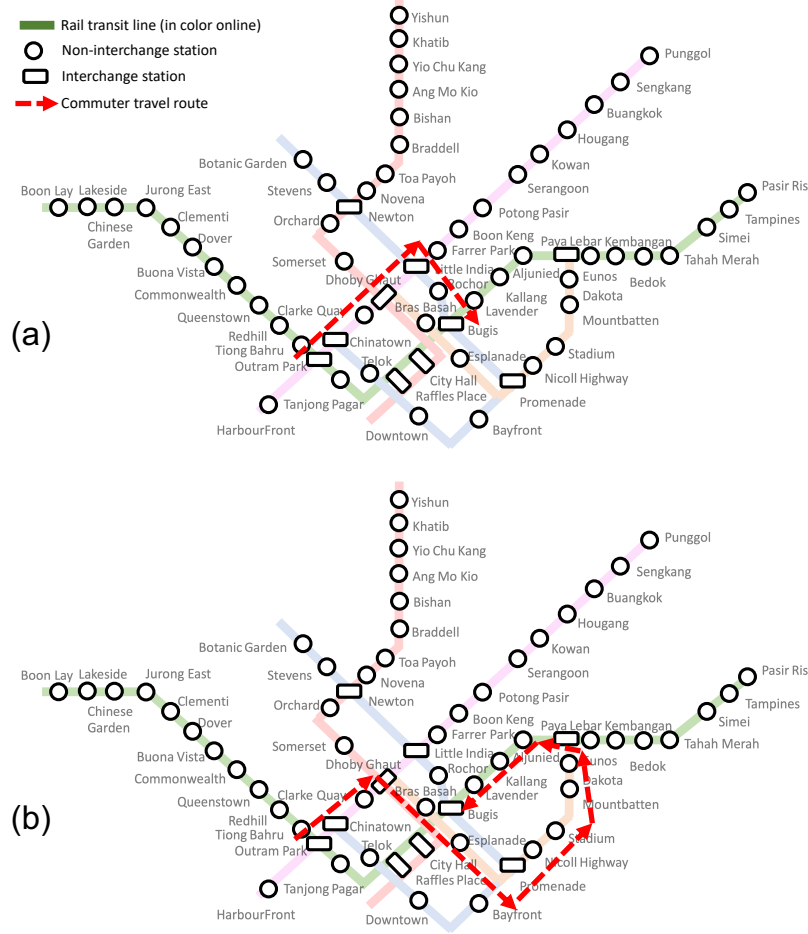


Figure 8: Travel route comparison before and after platform disruptions (note: platform Dhoby Ghaut (NE) is disrupted). (a) Initial travel route from origin platform Outram Park (NE) to destination platform Bugis (DT); (b) Identified contingency route from origin platform Outram Park (NE) to destination platform Bugis (DT) after platform disruptions.

5.2. System queue and outflows

With the consideration of contingency routes when disruptions occur, the system queue and total outflow can reveal the system performance in a more detailed manner. Figure 9 illustrates the queue and outflow of the Singapore case under malicious-degree strategy within an hour of observation. Subplot (a) shows the time-series system queue under multiple disruptions if without any recovery. It is clear that the serviceability would be severely deteriorated if there is no recovery whatsoever - by the end of 60 mins the system queue exceeds over 5300 and the total outflow of the system is only 4552. If the recovery strategy is considered

405

(subplot (b)) - recovering with degree-centrality-based sequence), we can see the overall system performance can be improved significantly. At the end of the observation, the system queue diminishes to 1506 and the accumulated outflow could reach 7688, which is a significant improvement of the serviceability of the rail transit system. 410

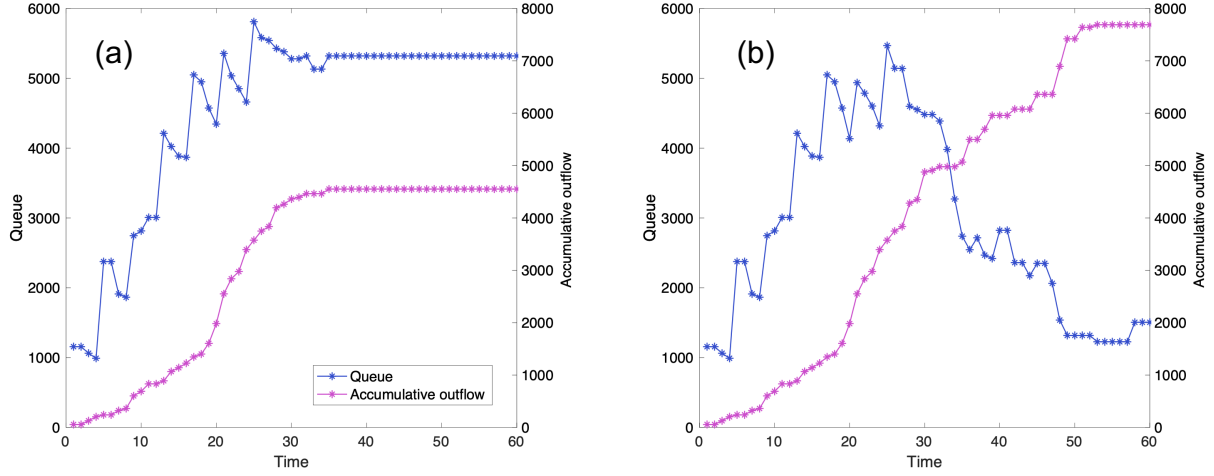


Figure 9: Comparison between the total queue and system outflow with malicious-degree strategy. (a) without recovery, and (b) with recovery. (Recall the simulation settings of attack and recovery stages in Section 4).

Figure 10 compares system queue and total outflow in four selected disruption-recovery scenarios. From subplot (a), it can be deemed that the peak of the system queue takes place around 30 mins after the commencement of the disruptions. Meanwhile, the total outflows of different scenarios are relatively converged at the beginning and then gradually diverged after 30 mins as well (subplot (b)). This indicates that this 30-mins timepoint is the turning point in the simulations, as all attacks are completed and the system is ready to recover from the impacts. We can see that the random-degree strategy has the worst performance among all, while others demonstrate a relatively more similar pattern in terms of both queue and outflow. Thus, it is necessary to have a closer look at all designed disruption-recovery scenarios to further understand their heterogeneous effect on system resilience. 415 420

5.3. Resilience assessment

Figure 11 demonstrates the resultant resilience curves of normalized system load in the Singapore case. The system performance drops no more than 45% on average (the drop is milder in the transfer-based scenarios). Apart from the malicious-transfer scenarios, all other scenarios demonstrate an insufficient post-event recovery curve by the end of the observation period, which indicates that the negative effects of the disruptions cannot be fully resolved within 60 mins of the observation time. Additionally, the system performance 425

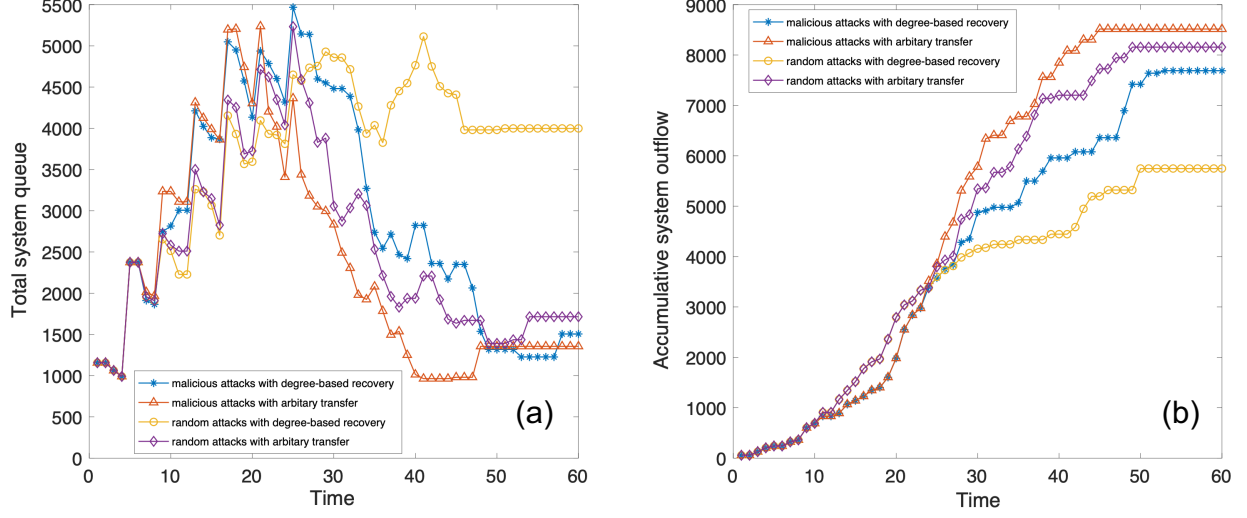


Figure 10: Total system queue (subplot a) and accumulative system outflow (subplot b) in selected scenarios. (Recall the simulation settings of attack and recovery stages in Section 4).

losses in the transfer-based recovery scenarios are overall much lessened than that of the topology-based recovery scenarios.

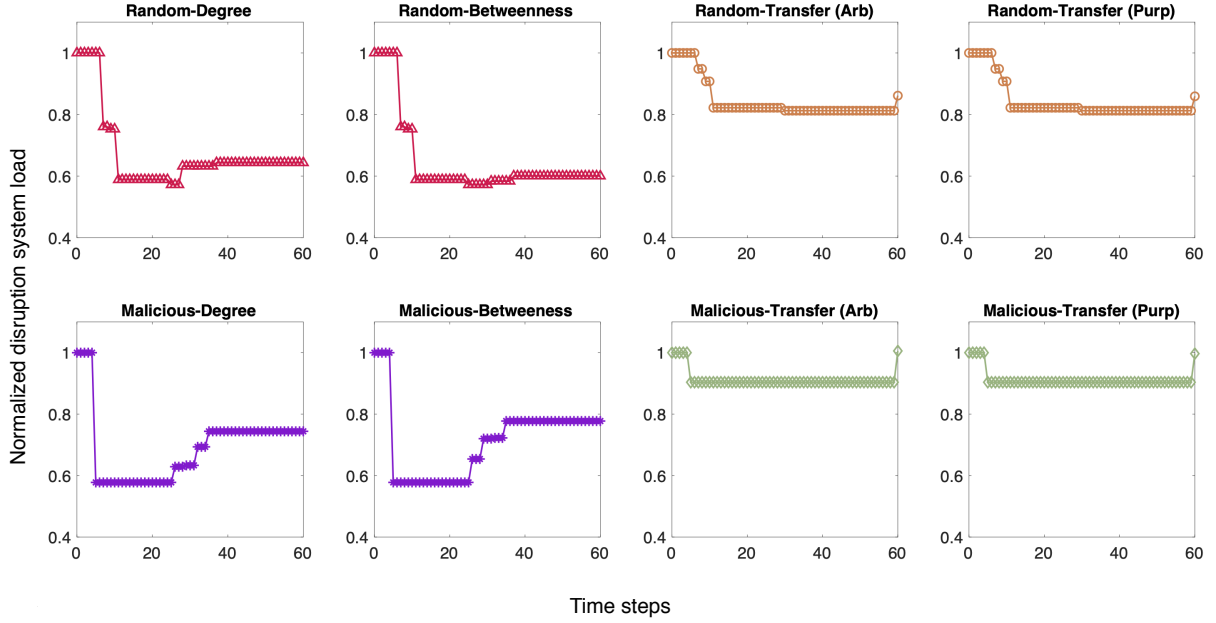


Figure 11: Random and malicious attacks with various recovery strategies of the rail transit system in Singapore case. (Recall the simulation settings of attack and recovery stages in Section 4).

To better understand the trends among the resilience curves, Figure 12 demonstrates the Pearson correlation analysis of all the curves from Figure 11. This correlation analysis helps to identify similar system behavior in different scenarios. It can be seen that random-based scenarios are all generally correlated with

high coefficients (more than 0.9). Such a strong correlation can only be found in those malicious-based scenarios with similar recovery strategies, i.e., malicious-degree and malicious-betweenness, and malicious-transfer (Arb) and malicious-transfer (Purp). By and large, the correlation strengths between different recovery strategies under malicious attacks are relatively weaker (between 0.7 to 0.8). The second observation is that the correlation strengths are significantly weak when comparing these two groups of attack scenarios.

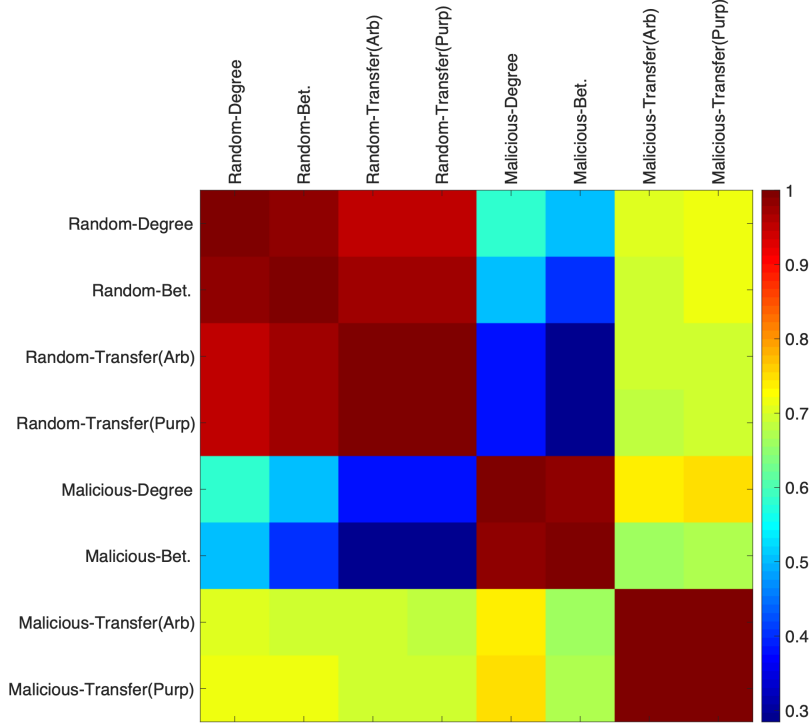


Figure 12: The correlation matrix of the eight disruption-recovery scenarios in Singapore case.

These features of the correlation observations can be further justified by the resilience quantification results. The calculated resilience indexes of the Singapore case are presented in Table 5. The highest resilience index (0.91) is obtained from malicious-transfer strategies, whereas the lowest resilience index (0.65) is resultant from the random-betweenness strategy. The average value of the resilience indexes is 0.78, which indicates a moderately high resilience level in this rail transit system.

Table 5: Resilience assessment results of the Singapore case

Disruption-Recovery	Degree	Betweenness	Transfer (Arb)	Transfer (Purp)
Random	0.67	0.65	0.84	0.84
Malicious	0.69	0.71	0.91	0.91

Intuitively, because of the nature of being deliberately targeted, the malicious attacks are generally considered to be able to cause more system performance loss than the random disruptions, leading to a

lower resilience level of the system functionality performance (Yin et al., 2016). However, we can see here that the malicious-based scenarios have slightly higher resilience indexes than that of the random-based scenarios. This counter-intuitive finding indicates that deliberately attacking the platforms at those interchange stations in this rail transit system does not necessarily lead to a drastic drop in system resilience. One possible explanation could be due to the locations of those interchange stations in the network (Lu, 2018). We find that those interchange stations are more concentrated around the city center area, and this results in a relatively closer distance between one interchange station to another. Such a shorter distance denotes a centralized layout of the interchange stations. When some of the centralized interchange stations are attacked and their platforms failed, it might only cause a mild burden to the system because commuters could take a fast contingency detour using other nearby interchanges.

When it comes to the comparison of different recovery strategies between topology-based and transfer-based scenarios, it is obvious that the system is relatively more resilient if restoring with the transfer-based recovery strategies. In both random and malicious attacks, the system resilience is improved by approximately 30% on average by switching recovery strategy from topology-based to transfer-based, i.e., providing bus-bridging services. On the other hand, there are no such significant differences within each recovery scenario group, because under the same type of attacks the differences between degree- and betweenness-based recovery strategies are fairly subtle, and the arbitrary and purposeful transfer strategies yield exactly the same resilience indexes according to the overall disruption system load. This interesting finding suggests that, under the designed disruption-recovery scenarios, the differences between the detailed recovery scenarios within the same recovery strategy group could be trivial.

5.4. Comparative case analysis

Figure 13 demonstrates the resilience curves under the same disruption-recovery scenarios in the Chongqing case. In this case, all disruption-recovery scenarios have an insufficient post-event recovery performance, which indicates that the negative impact on disruption system loads is worse than that of the Singapore case. One obvious difference between these two case studies is that the resilience indexes in the Chongqing case comply with one’s intuition, as its malicious-related scenarios have a generally lower resilience than the random-related scenarios. As discussed, this might be a result due to the geographical locations of the interchange stations in the network. The interchange stations in Chongqing’s rail transit system are more sporadically distributed within the entire system (de-centralized layout). Because those interchange stations are distant from each other, when their platforms failed, commuters need to take longer to detour and eventually exit at the destinations, leading to a worse system performance in terms of the disruption system load. In other words, this comparative finding implies that the interchange stations of the rail transit system in

Chongqing are more critical, with respect to system resilience, in such a de-centralized layout than those in a centralized layout such as the Singapore case.

Despite this difference, these two case studies demonstrate high commonalities in the overall patterns as well. Specifically, it can be seen that the curves from the transfer-based strategies have less performance loss comparing with the topology-based scenarios under both random and malicious attacks. The differences between the scenarios of the same type of attacks are not significant in the Chongqing case neither, which indicates that, in our specific simulation scenarios, either arbitrarily providing bus-bridging services or managing the services purposefully does not significantly alter the system resilience under multiple disruptions.

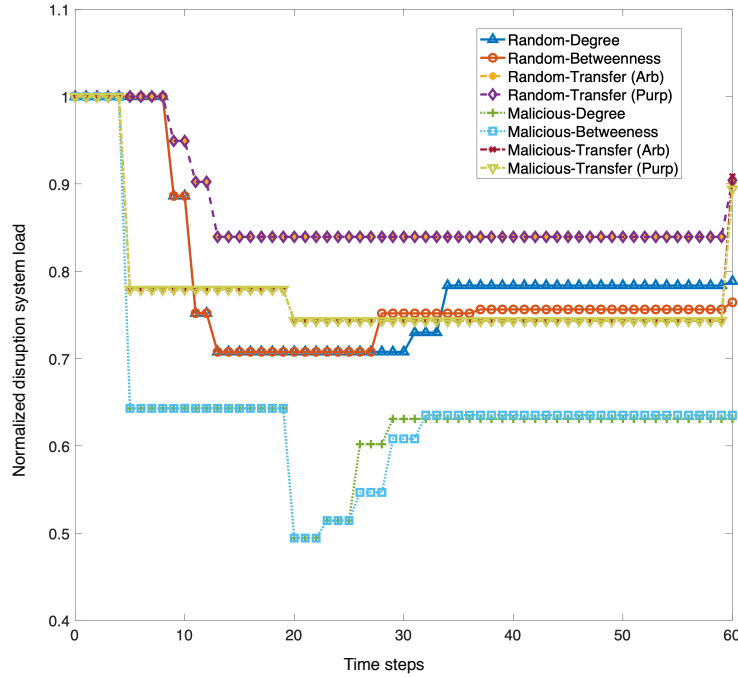


Figure 13: Random and malicious attacks with various recovery strategies with NORMAL travel demand in Chongqing metro system

From Table 6, we calculate the average resilience of the Chongqing rail transit system is about 0.77. However, the overall improvement of resilience by switching from topology-based recovery to transfer-based recovery drops from 30% (Singapore case) to 14% here, which demonstrates an obvious heterogeneous effect of providing bus-bridging across these two case studies. Thus, with the distinct characteristics in terms of system topology, while it is clear that providing transfer-based replacement services as a recovery strategy can improve system resilience, we still admit that the effectiveness of this recovery strategy varies for different systems. i.e., a one-size-fits-all solution for providing bus-bridging services to rail transit disruption management might not be appropriate, and finding the optimal bus-bridging strategy would be highly context-dependent from case to case.

Table 6: Resilience assessment result of Chongqing case studies

Disruption-Recovery	Degree	Betweenness	Transfer (Arb)	Transfer (Purp)
Random	0.79	0.78	0.87	0.87
Malicious	0.65	0.65	0.77	0.77

5.5. Sensitivity on total travel demands

Sensitivity tests are not uncommon in traffic simulation and transport modeling studies. We test the sensitivity of the numerical simulations against different levels of total travel demands and verify whether or not the resilience of the systems would change dramatically. The reason is two-fold: (1) the daily average of the total travel demand in these two cities can be fundamentally different due to many factors (e.g., population size), thus, additional comparative analysis with demand variations is needed; (2) varying total demand can also capture some essential yet hidden characteristics of the system under different temporal scales, such as peak time and off-peak time.

Two levels of total travel demands - low and high - are tested here (recall section 3.4). The resilience curves for both city cases with lower and higher demands are presented from Figure A1 to Figure A4 in the appendix. The corresponding numerical values are shown in Table 7 and Table 8. In the Singapore case, the change from normal to high demand yields a slightly lower system resilience in all of the scenarios, and at low demand, the resilience indexes of random-transfer scenarios slightly rise. Both Singapore and Chongqing cases demonstrate a certain level of robustness in this sensitivity test, as the overall comparative trends and characteristic patterns between groups of disruption-recovery scenarios do not change drastically while the total demand changes, i.e., the findings about the overall patterns in the previous sections can be considered stable.

Table 7: Sensitivity resilience assessment result against low demand

Singapore				
Disruption-Recovery	Degree	Betweenness	Transfer (Arb)	Transfer (Purp)
Random	0.64	0.63	0.85	0.85
Malicious	0.65	0.67	0.90	0.90
Chongqing				
Disruption-Recovery	Degree	Betweenness	Transfer (Arb)	Transfer (Purp)
Random	0.75	0.77	0.86	0.86
Malicious	0.63	0.62	0.78	0.78

6. Managerial implications and limitations

The concept of resilience provides an alternative lens for addressing disruption management and paves a promising pathway for achieving reliable and safe urban rail transit systems. From the result and discussion,

Table 8: Sensitivity resilience assessment result against high demand

Singapore				
Disruption-Recovery	Degree	Betweenness	Transfer (Arb)	Transfer (Purp)
Random	0.66	0.65	0.79	0.79
Malicious	0.66	0.68	0.89	0.90
Chongqing				
Disruption-Recovery	Degree	Betweenness	Transfer (Arb)	Transfer (Purp)
Random	0.82	0.82	0.89	0.89
Malicious	0.71	0.68	0.79	0.79

there are two managerial implications that could be extrapolated. Firstly, the comparison between the rail transit systems in Singapore and Chongqing reveals a counter-intuitive and largely overlooked observation, that is, the deliberate attacks on the platforms of the interchange stations might not always lead to worse system resilience. The interchange stations of a rail transit system intuitively play crucial roles in creating the shortest paths and maximizing connectivity in multiple transit lines. When multiple disruptions occur, it is intuitive to pay more attention to those interchange stations in a rail transit system. However, what we found from the results is more like a potential caveat for some of the cities, such as Singapore, whose rail transit system has more centrally distributed interchange stations within a certain area. From the results, restoring the disrupted platforms of those interchange stations with high priority might only have a very limited contribution in terms of improving system resilience. But, for a rail transit system like the one in Chongqing, paying more attention to those sporadically distributed interchange stations to improve the system resilience seems more reasonable. One previous study found that the criticality of stations is dynamic and dependent on characteristics of disruptions and stations, and the geographical location of the station and the redundancy of rerouting alternatives (Lu, 2018). To some extent, the result from this previous study supports our findings and observations here in this paper (even though we are focusing on disruptions at the platform level). Besides, considering the fact that the network designs of rail transit systems are usually subjected to various constraints, including technical feasibility, cost and budget, and public opinions. Thus, it is inherently a case-by-case issue to determine how the resilience of a rail transit system can be improved in terms of optimized commuter flows under multiple disruption events, i.e., a dynamic and tailored recovery strategy should be considered.

Secondly, with the model being extended and improved with the consideration of walking time during transfers, the system performance that incorporates contingency routing, queues, and disruption system load can be comprehensively manifested. As if demonstrated in real-world practice, the comparative findings also quantitatively confirm that providing transfer bus services (or other ad-hoc connecting services such as taxi (Zeng et al., 2012)) for the disrupted platforms is an effective measure to restore system resilience. From the results, it is clear that the system behaves differently under distinct types of attack-recovery

scenarios (even though such difference was not very significant between similar recovery strategies under the same attack scenario). We, therefore, suggest that specific bus-bridging plans should be tailored in the contingency agenda by city managers and policymakers according to different types of disruptions, and more importantly, such plan should be made based on a dynamic approach rather than a deterministic and static manner.

Last but not the least, we also acknowledge the following limitations in this study: (1) The design of the disruption-recovery scenarios can be expanded by incorporating more detailed and practical factors. For example, the system resilience under cascading failures of the platforms with different failure and recovery rates can be further explored; (2) Due to the issue of data availability, this study is a theoretically numerical investigation, which might need to be further compared with empirical data.

7. Conclusions

This paper assesses the performance-based resilience in urban rail transit systems with optimized flows and bus-bridging services under multiple disruptions on platforms. The rail transit system in Singapore is used as the main case study in the numerical study, and the Chongqing case study is used as an analog to further extract insights from this comparative study. A linear programming model is extended with improvements, and a set of disruption-recovery scenarios are designed to carry out the disruption and resilience simulations. From the results, several managerial implications and limitations are extrapolated and acknowledged. Two major conclusions can be summarized as follows.

Firstly, as interchange stations play critical roles in rail transit systems in terms of creating connectivity, intuitively, failures of the platforms at interchange stations would lead to a resilience drop. However, this might not always hold as we found in the Singapore case that attacking those interchange stations, and thus disabling the transfer platforms, does not result in an extensive resilience loss. As compared to the Chongqing case, different geographical distribution and configurations of the interchange stations would impact the level of system resilience. Next, the numerical simulation results of the two case studies showed that the effect of bus-bridging recovery, in terms of improving the system resilience, could vary from 14% to 30% on average under the designed disruption-recovery scenarios. And this positive enhancement effect is robust against changes in total travel demands, indicating that this recovery strategy has relatively stable superiority in resilience-building management against the uncertainties brought by travel demand. However, the results also indicate that there is no one-size-fits-all solution plan for designing transfer-based recovery strategies in different rail transit systems, and thus, we suggest that specific bus-bridging plans should be tailored and made based on a dynamic manner. This study enriches the resilience assessment toolbox and sheds new

light on the transfer-based recovery strategies for building resilience in urban rail transit systems, as well as 570
provides insightful implications for stakeholders and decision makers in system planning and management.
The future work will focus on addressing the acknowledged limitations and revealing more unexplored factors
influencing system resilience in urban rail transit systems.

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Appendix

In this appendix, the resilience curves of the sensitivity tests for both case studies can be found from 580
Figure A1 to Figure A4. The method for generating those figures is the same as the approach described in
the methodology section.

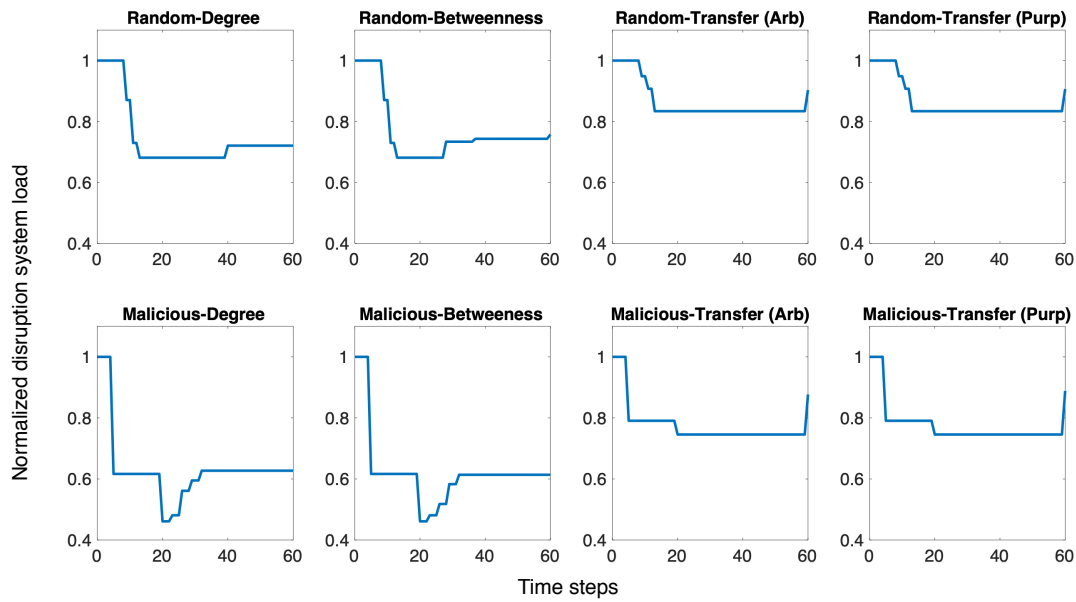


Figure A1: Random and malicious attacks with various recovery strategies with LOW travel demand in the Chongqing case

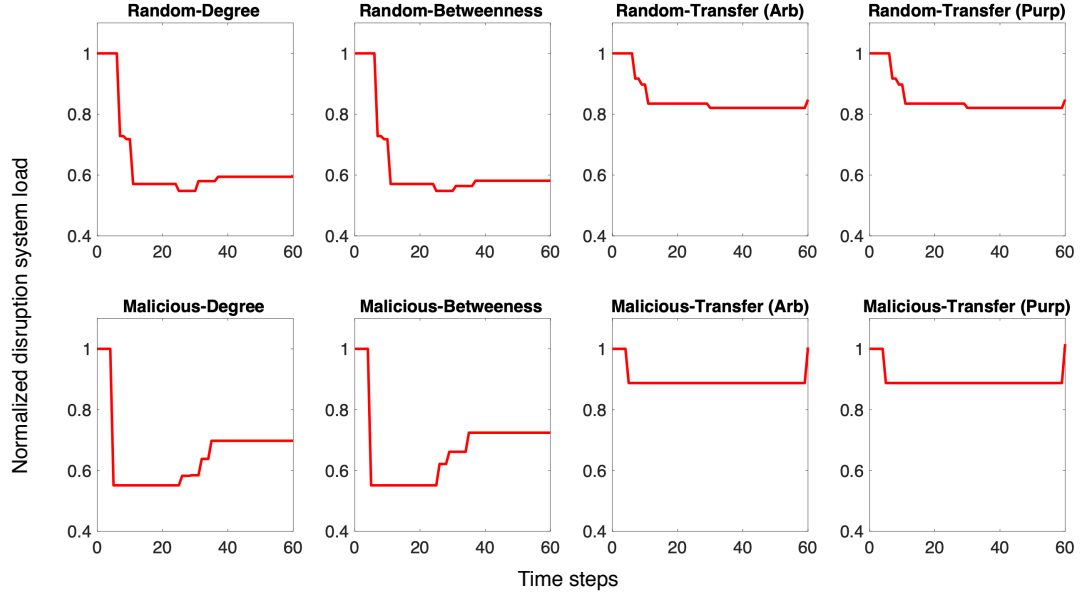


Figure A2: Random and malicious attacks with various recovery strategies with LOW travel demand in the Singapore case

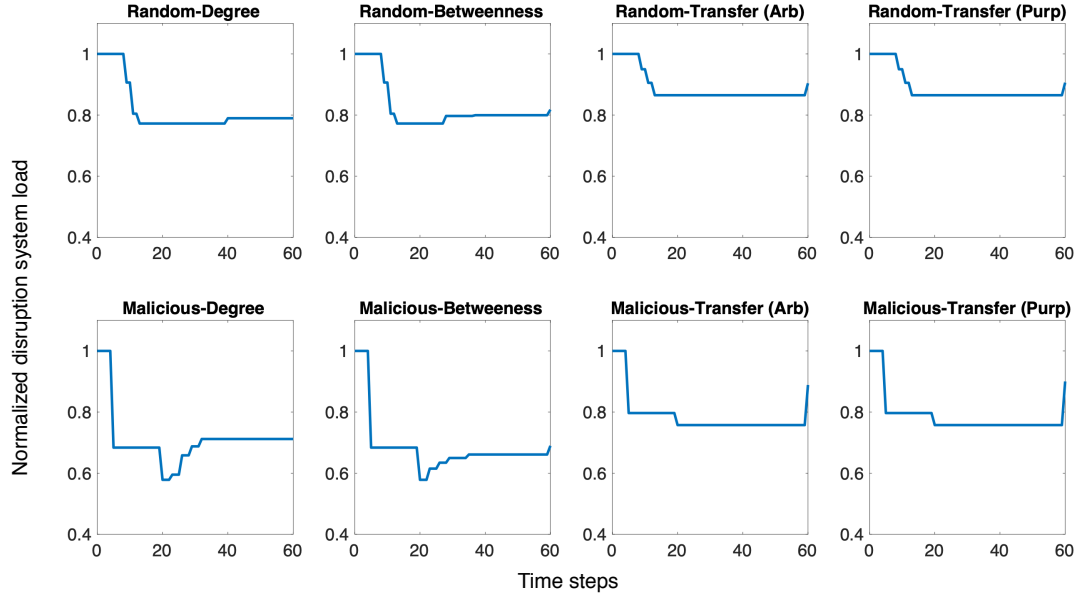


Figure A3: Random and malicious attacks with various recovery strategies with HIGH travel demand in the Chongqing case

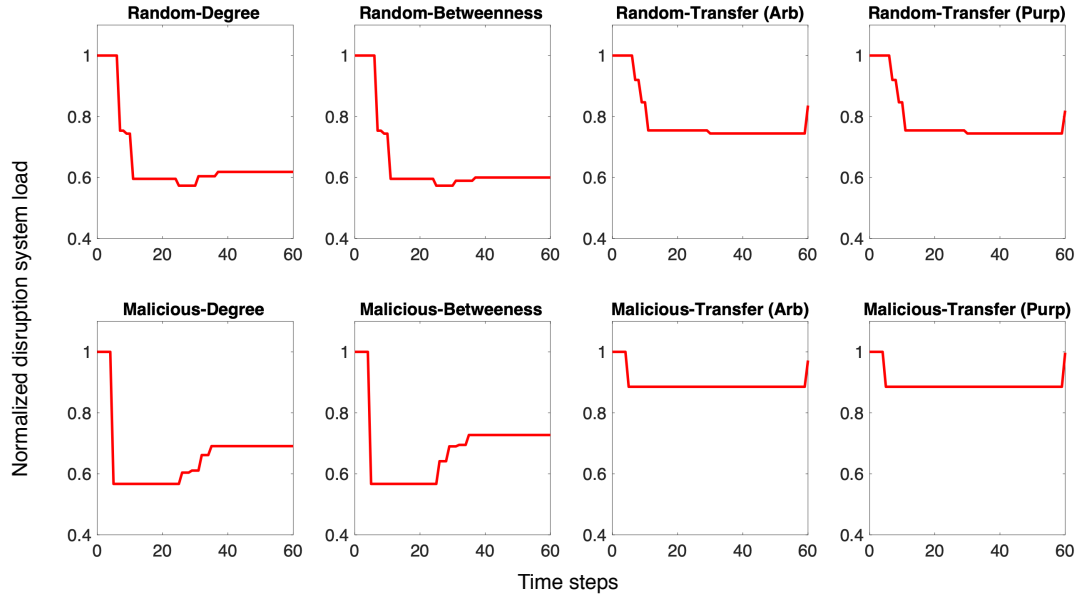


Figure A4: Random and malicious attacks with various recovery strategies with HIGH travel demand in the Singapore case

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