Benchmark Analysis for Robustness of Multi-Scale Urban Road Networks Under Global Disruptions

Wen-Long Shang, *Member, IEEE*, Ziyou Gao, Nicolò Daina, Haoran Zhang, Yin Long, Zhiling Guo* and Washington Y. Ochieng

***Abstract*— To date immunity to disruptions of multi-scale urban road networks (URNs) has not been effectively quantified. This study uses robustness as a meaningful - if partial - representation of immunity. We propose a novel Relative Area Index (RAI) based on traffic assignment theory to quantitatively measure the robustness of URNs under global capacity degradation due to three different types of disruptions, which takes into account many realistic characteristics. We also compare the RAI with weighted betweenness centrality, a traditional topological metric of robustness. We employ six realistic URNs as case studies for this comparison. Our analysis shows that RAI is a more effective measure of the robustness of URNs when multi-scale URNs suffer from global disruptions. This improved effectiveness is achieved because of RAI's ability to capture the effects of realistic network characteristics such as network topology, flow patterns, link capacity, and travel demand. Also, the results highlight the importance of central management when URNs suffer from disruptions. Our novel method may provide a benchmark tool for comparing robustness of multi-scale URNs, which facilitates the understanding and improvement of network robustness for the planning and management of URNs.**

***Index Terms*—Benchmark analysis, Global disruptions, Immunity, Robustness, Urban road networks.**

I. Introduction

Health examination (HE) of urban transportation is a relatively new concept along with the establishment of urban physical examination, which is first proposed in Beijing urban master plan (2016-2035) [1]. As an important aspect of HE, the ability of URNs to maintain normal operation when suffering from disruptions, that is, immunity of urban transportation to disruptions is receiving more attention.

Urban road networks (URN) are crucial infrastructure components of urban transportation and constitute an essential backbone underpinning most social and economic activities [2,3]. Road traffic networks and infrastructure are vulnerable to disasters [4-6], however, some of which, like extreme weather events or earthquakes, can be so disruptive as to lead to a complete system failure [7, 8]. In such circumstances the direct loss of life and economic loss arising from the disaster event itself are supplemented by indirect losses resulting from delays caused by the inability of emergency services and humanitarian agencies to use the road network effectively [4, 9].

Against this background, it is important to assess the level of immunity of URNs to major or global disruptions. Robustness of URNs is the traditional concept that the transportation planning community adopts to indicate the level of immunity. However, to the best of our knowledge, quantitative indices that assess and compare the ability of URNs to withstand global disruptions are deficient because they fail to account for all the attributes (road capacity, drivers' behavior and flow patterns) that enable a realistic representation of URNs and do not allow the comparison between multi-scale URNs under global disruptions. In this study, multi-scale URNs refer to the road networks with significant differences in the number of nodes and links.

The differences in types of network, the infrastructure they use and in the constraints and objectives applied to those networks have meant that it has been difficult for scholars to agree on a definition of what "robustness" actually means in the context of networked systems. In the context of electrical networks, robustness has been defined, variously, as "the degree to which a system or component can function correctly in the presence of invalid inputs or stressful environmental

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conditions” [10] and “the ability to keep the network structure (function) intact when exposed to perturbations” [7]. In [11], Immers et al. consider robustness to be “the degree to which a system is capable of functioning according to its design specifications in the case of serious disruptions”. In [12], Boccaletti et al. define it a network’s ability to continue to operate when a proportion of its constituent elements are damaged. In [13], Schillo et al., meanwhile, define robustness as the ability to maintain “safety responsibilities”, although they also see this as being related in a broad sense to system performance. In the context of URNs, robustness is defined in this study as the ability of a system to maintain its original performance when experiencing disruptions. It is also noteworthy that there are similarities between robustness and resilience. They both do not have unified definitions due to the diversity of network systems, and are both related to the ability of a system withstanding internal/external disturbances. However, they have significant differences. Robustness focuses on the ability of a system to maintain its original performance, which is inherent and static, while resilience emphasizes on the ability to ‘bounce back’ to the normal state of the system [14, 15].

There are many measures of robustness related to road networks, and the number of studies related to robustness of road networks is considerable relatively, which mainly focuses on either topology-based or traffic-based models. So far, however, no quantitative assessments of the robustness of URNs with different sizes have been able to capture the realistic features of networks experiencing global disruptions. Based on this, a relative area index (RAI) is proposed to conduct such benchmark analysis of multi-scale URNs, in order to examine the ability, namely, immunity of URNs against global disruptions.

The contribution of this paper is to propose a benchmark index, the relative area index (RAI), that can be used to measure the robustness of multi-scale URNs against different types of global capacity degradation. The RAI quantitatively captures the networks’ ability to withstand internal or external global disruptions, and to keep performing at a satisfactory level. Based on this, the benchmark analysis of the robustness is conducted for six selected realistic urban road networks. Three types of weight parameters are utilized to model the nature of different global disruptions, and, in common with other network topological assessments of robustness, Spearman’s ranking correlation test is applied to reveal potential correlations between proposed indices and weighted betweenness centrality. The aim of this study provides an effective tool for benchmark management of robustness planning on urban infrastructure against global disruptions, so as to facilitate the understanding to health state and immunity of URNs.

The paper is structured such that section 2 reviews previous work on the measurement of robustness, encompassing both the topological and operational sides of that question, and classifications of disruptions. Following this, section 3 explains the concepts and methodological approaches applied in this research, including weighted betweenness centrality and the relative area index based on User Equilibrium (UE) and System Optimum (SO) principles. Section 4 then presents a case study analysis to benchmark six urban road networks. Section 5 concludes the study, and discusses future works.

II. Literature Review

Until recently there was relatively little research into the robustness of transport networks to disruptions [16]. Nonetheless, the number of studies related to robustness of transport networks is now considerable. These mainly explore robust characteristics of networks based on either the topology of networks or traffic-based models. We review the literature on robustness in transport networks within these two classes. In addition, we also review the disruptions which may cause the negative impacts on URNs, so as to understand how they affect URNs.

A. Robustness based on topology

Topological indices of the robustness of networked systems focus on the network topology of networks without taking into account the distribution of any quantity transported by the network. Topological indices are based on complex network theory and include measures such as degree centrality, clustering coefficient, betweenness centrality, and the size of the largest connected component [17]. In essence these measures aim to reflect how efficiently the underlying network functions [18-22], and in that sense they are intrinsically also measures of robustness. In [23, 24], Shang et al. and Callaway et al. explain these indices more fully.

In [22], Albert et al. consider measures such as the change of diameter, the size of the largest cluster and the average size of isolated clusters as means of assessing the tolerance of networks to disruptions, whether deliberate or random. In [18], Holme et al. find that removing nodes from complex networks in a descending order of recalculated degree and betweenness has a more adverse effect on robustness than when nodes are removed in a descending order of initial degree and betweenness. Similarly, in [19], Crucitti et al. focus on shortest paths as a measure of the efficiency of simulated networks, in [25], Crucitti et al. examine the consequences for the global efficiency of electric networks when nodes are either removed randomly or in descending order from the largest load. In the context of road networks, meanwhile, in [26], Sakakibara et al. propose a topological index based on network dispersiveness/concentration to evaluate robustness in disaster situations, aiming to minimize the isolation of districts in such circumstances. In [27], Sun et al., meanwhile, focus on betweenness: i.e. the measure of how often a given node is on the shortest route between any pair of nodes. They show how the robustness of an air traffic control network can be measured using a statistical distribution of the betweenness of all the nodes in that network. Specifically, they argue that networks with a higher number of nodes with small betweenness will be more robust against individual failures than a network with fewer such nodes.

To identify the critical factors, in [28], Wang et al. utilize the area of radar diagrams for ten topological metrics to assess overall robustness of 33 realistic metro networks, as a result, transfer stations and long link sections are identified as two important factors of robustness of metro networks. In [29], Clark et al. have developed an approach to assess robustness and resilience of National Airspace System (NAS), the relative size of largest connected cluster in the NAS is used to quantify the tolerance to loss of critical functions, and they demonstrate that centrality measures are a good platform for supporting restoration. In addition, in [30], Zhang et al. explore the robustness and vulnerability of Shanghai metro network by calculating its network efficiency from topological perspective when removing nodes.

Although many studies into network robustness, such as those above, adopt topological approaches to the problem, topological indices are unable to capture realistic capacity, traveler behaviors and flow patterns in urban road networks (URNs).

B. Robustness based on traffic-based models

In the context of URNs, therefore, operational indices are also often used to measure robustness. These take into account travel demand, driver behaviors [31] and link capacity. In this strand of the studies, in [32], Scott et al. proposed a new Network Robust Index (NRI), encompassing network flows, link capacity and network topology. This seeks to locate the links that have the most impact on the efficiency of a network by estimating the overall impact on travel time as individual links are removed from the network. This study then compares the results from the NRI calculation to those of the traditional measure of critical links, the volume/capacity (V/C) ratio, revealing that NRI provides better planning solutions for congested networks than V/C. In [33], Sullivan et al. extend the earlier work by proposing the Network Trip Robustness (NTR) as a measure of the system-wide robustness of transportation networks in circumstances where links experience reductions in capacity. In [34], Nagurney and Qiang, meanwhile, propose a network efficiency measure by capturing demand, flows, costs and user behaviors from a traffic user equilibrium model, and then use the measure to access the robustness of transport networks and rank the impact of individual links on the efficiency of the whole network. In their subsequent work [35], Nagurney and Qiang then use the relative change in the proposed measure as a proxy for the robustness of the network to a gradual reduction in the capacity of all its links. Indeed, this study focuses on degrading link capacity rather than removing links, which distinguishes Nagurney and Qiang's work from that other previous studies. Thereafter, in [36], Nagurney and Qiang develop another measure of robustness to degraded network links, which they dub the "relative total cost index". That approach picks up the travel behaviors associated with User Optimization (UO) and System Optimization (SO) to derive the overall cost of a given journey. In [37], Zhao et al. utilize this relative total cost index based on stochastic user equilibrium to investigate the robustness and Braess paradox of networks.

Although there are not many measures of robustness based on operational indices, they are able to apprehend features such as travel demand, link capacity and driver behavior more realistically. In addition, the quantitative measures of robustness of road networks with different sizes against global capacity degradation are highly insufficient.

TABLE I
CATEGORIES OF ROAD DISRUPTIONS

	Frequent	**Unusual**
Predicted	Predictable changes in supply and demand, planned or regular maintenance	Major public events, bad weather, strikes
Unpredicted	Minor road traffic accidents, facility failures	Natural disasters, deliberate damage or hostile acts (e.g. terrorist, military or cyber attacks)

C. Classification of disruptions

There have been many studies into disruptions of URNs, such as transit strikes [38-40], bridge closure/collapse [41-43], special events [44, 45] and earthquakes [46-48]. Broadly, these disruptions can be categorized as expected or unexpected in nature [49,50], and as occurring in a regular, predictable way, or not [11]. **TABLE I** that categorizes potential disruptions is shown below.

While all these disruptions have the potential to result in the poor functioning of URNs, and some may even result in a risk of system collapse[51], this study focuses on those that have the potential for more serious effects on the road infrastructure, i.e. those that could negatively affect an URN at global level. These disruptions include extreme weather conditions and other natural calamities [52]. Furthermore, these disruptions affect transport networks in different ways: some, such as torrential rain, lead to reduce capacity, while others, such as an earthquake, may remove nodes/links[53].

Based on above review, this study mainly concentrates on the disruptions which impact the URNs by means that may cause a global capacity degradation. The study specifically seeks to examine the inherent robustness of URNs against global disruptions caused by extreme weather condition or natural calamities that have the potential to cause high levels of destruction to the road infrastructure.

III. METHODOLOGY AND DATABASE

The methodology applied in this study is (1) to use the proposed relative area index (RAI), derived from user equilibrium (UE) and system optimum (SO), to quantify the robustness of URNs; and (2) to use weighted betweenness centrality (WBC) as a baseline.

In order to show the calculation process of RAI in full, the UE and SO is quickly recapped, although the discussions of them are standard. More detailed information is referred to [54] and [55].

A. The relative area index under distinct principles

Assuming in a directed network $G(N, A)$, N is a set of nodes, A is a set of links, W is a set of origin-destination (OD) pairs, $(i, j) \in W$ indicates a specific OD pair and T_{ij} is fixed travel demand. In addition, the paths for OD pair $(i, j) \in W$ is the set P_{ij}, the unit travel cost to complete path $p \in P_{ij}$ is c_p, and the flow on path p is represented as h_p.

The link flows, f_a, are associated with the path flows and are represented in the equation:

$$f_a = \sum_{p \in P} \delta_{ap} h_p \quad \forall a \in A \tag{1}$$

where δ_{ap} is a link-path incident matrix:

$$\delta_{ap} = \begin{cases} 1 & if\ a \text{ belongs to } p \\ 0 & if\ a \text{ does not belong to } p \end{cases}$$

The cost of travelling on a given path in the network is articulated in (2):

$$c_p = \sum_{a \in A} \delta_{ap} c_a(f) \quad \forall p \in P \tag{2}$$

In the above, $c_a$is a unit cost function that is intrinsically dependent on the flow along the link—represented as $f = (f_a : a \in A)$. This is then combined with the well-known US Bureau of Public Roads [56] (BPR) link performance function to create the link function shown in (3):

$$t(f_a) = t_a \left(1 + \alpha \left(\frac{f_a}{K_a}\right)^{\beta}\right) \quad \forall a \epsilon A \tag{3}$$

where f_a denotes flows on each link $a \in A$, t_a and K_a are, respectively, the free flow travel time and capacity of link a; and α, β are positive constants.

The following flow conservation must hold:

$$T_{ij} - \sum_{p \in P_{ij}} h_p = 0 \quad \forall (i, j) \in W \tag{4}$$

Then the set of feasible flows is shown below:

$$\gamma = \left\{ h \geq 0 : T_{ij} - \sum_{p \in P_{ij}} h_p = 0 \ \forall (i, j) \in W \right\} \tag{5}$$

As (5) describes, the sum of the flows across all the individual paths of the O-D pair (o, d) equates to the overall travel demand for the (o, d).

1) Total cost under User Equilibrium (UE)

The Wardrop [57] proposed a principle that a certain equilibrium is reached when individual drivers selfishly pursue the maximization of their personal interests. This concept, often referred to as "User Equilibrium" (UE) can be expressed mathematically using the optimization below [58].

$$Min\ Z = \sum_a \int_0^{f_a} c_a(f_a) df \tag{6}$$

Subject to

$$\sum_{p \in P_{ij}} h_p = T_{ij} \quad \forall (i, j) \in W \tag{7}$$

$$f_a = \sum_i \sum_j \sum_p \delta_{ap}^{ij} h_p^{ij} \quad \forall a \in A \tag{8}$$

$$\begin{aligned} h_p^{ij} &\geq 0 \quad \forall p \in P_{ij}, \forall (i, j) \in W \\ f_a &\geq 0 \quad \forall a \in A \end{aligned} \tag{9}$$

The total cost (TC_{UE}) of travel in a network that is at its user equilibrium is given by:

$$TC_{UE} = \sum_{a \in A} f_a^* c_a(f_a^*) \tag{10}$$

The equations above include the objective (6), and a series of constraints, respectively, for conservation (7) and (8), and non-negative flows (9). The link cost function increases monotonically such that the link flow pattern of UE is unique [59] and the objective of the program is convex. A fixed point algorithm (FPA) is applied to the calculation of UE solutions f_a^*. For the detailed procedure for this refer to [55].

2) Total cost under System Optimum (SO)

Another significant contribution by Wardrop [57] lies in his second principle of traffic assignment: System Optimum (SO). This is the process whereby centralized controllers assign drivers to routes in such a way as to minimize the total travel costs incurred by all drivers [60]. The System Optimum can be expressed mathematically using the nonlinear optimization below:

$$Min\ Z = \sum_a f_a c_a(f_a) \tag{11}$$

Subject to

$$\sum_{p \in P_{ij}} h_p = T_{ij} \quad \forall (i, j) \in W \tag{12}$$

$$f_a = \sum_i \sum_j \sum_p \delta_{ap}^{ij} h_p^{ij} \quad \forall a \in A \tag{13}$$

$$h_p^{ij} \geq 0 \qquad \forall p \in P_{ij}, \forall (i,j) \in W$$
$$f_a \geq 0 \qquad \forall a \in A$$

Here, the total cost (TC_{SO}) of travel in a network that is at its system optimum is given by:

$$TC_{SO} = \sum_{a \in A} f_a^* c_a(f_a^*) \tag{14}$$

In this study, FPA is used to calculate the SO solutions f_a^*.

3) Robustness key performance indicator (KPI): Relative Area Index (RAI)

We use the above principles of UE and SO as the basis for our proposed Relative Area Index (RAI) to explore the robustness of multi-scale URNs.

Various levels of capacity degradation for global URNs are taken into account. Let u be a *capacity degradation parameter* (CDP) between u_0 and u_c. When u is equal to u_0, URNs do not suffer from any disruptions and the capacity of URNs stays maximum. u_c denotes URNs that are subject to a capacity degradation level which may cause a significant increase of total travel cost. Furthermore, $TCE(u)$ is denoted as the curve of total cost based on equilibrium state of URNs suffering from capacity reduction of u, which can be calculated by (6)-(10) and (11)-(14) according to different equilibrium principles: UE and SO. Some examples that depict the evolution of network performance under different levels of global disruptions are shown in Fig. 1 below.

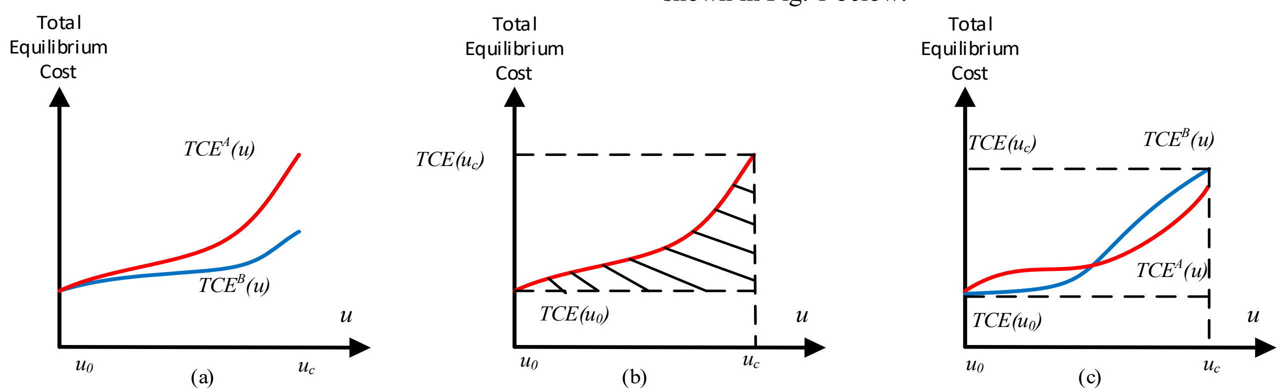

Fig. 1. (a): two examples of the function $\boldsymbol{TCE(u)}$: the lower (blue) is a more robust network than the upper (red) one. (b): illustration of the relative area (the ratio of the shadowed area to the area within the box) as an indicator of by how much the network capacity is reduced. (c): illustration that some form of weighting is needed since two different curves can return the same relative area.

In order to capture and quantify deterioration of global capacity of URNs, we consider the area formed by the $TCE(u)$ curve. The two line segments (Fig. 1**.** (a)) represent different evolution curves of total cost for different URNs suffering from global disruptions. Two functions, $TCE^A(u)$ and $TCE^B(u)$ corresponding to URN A and URN B, show that URN B is more robust than URN A. The shadow area (Fig. 1. (b)) reflects how much the network-level cost deviates from the original performance (total cost without disruptions) as the network capacity is reduced. Therefore, the smaller the shadow area is, the more robust the URN is against global disruptions. Because two different $TCE(u)$ curves may yield the same area (Fig. 1. (c)), a weighting parameter $w(u)$ is introduced to distinguish such case. $w(u)$ can be assigned different values which depends on the types and nature of disruptions. For example, if the global disruptions are caused by daily maintenance, the capacity degradation is mild, and the smaller weights will be assigned to $w(u)$ with larger u. Therefore, as shown in graph (c) of Fig. 1, the city A (red line) has a larger weighted area than city B (blue line) and thus is less robust. In this study, three types of weighting parameters are used. The first type assigns the equal values to $w(u)$, which corresponds to the disruptions that may impact URNs to the same extent as network capacity deteriorates, such as regular maintenance activities. The second type assumes that the larger weights correspond to the smaller values of u, and this type of disruptions tend to cause the cascading failure, such as traffic accidents at the critical parts of URNs. The third type assumes that the larger values of u use higher weights, which is related to the disruptions that have accumulative impacts on URNs, such as continuous rainfall or snowfall. These three types of weighting parameters can reflect the different ways that disruptions impact URNs, and will facilitate the exploration of robustness of URNs against global capacity degradation. Following this, Relative Area Index (RAI) for URNs is formulated as follows:

$$RAI = \frac{\int_0^u w(u)[TCE(u) - TCE(0)]du}{\int_0^u w(u)\, TCE(0) du} \tag{15}$$

The numerator of (15) is the weighted area with weights, which measures how much the curves deviate from the original performance of URNs at equilibrium state. The equation's denominator, however, serves to normalize the area. This makes it possible to examine by how much the performance of a road network has reduced compared to its undisturbed performance. For a given URN, the larger the RAI is, the greater the increase in the cost associated with the URN when the network capacity drops, thus the URN is less robust for global disruptions. In the study, we utilize the total travel cost and relative area to measure the performance and robustness of URNs, respectively, and (15) is able to illustrate the relationship between network performance and the robustness of URNs well.

Since the RAI used in this study is based on UE and SO principles, the proposed index can be divided into RAI-UE and RAI-SO respectively.

This RAI index is very similar to an index proposed by [23]. The latter index is more focused on the capacity reduction at the nodal level and is based on the maximal flow model of European air traffic network, whereas this novel RAI is based on the UE and SO traffic model of URNs and more concentrates on the robustness of URNs suffering from global disruptions at network level.

B. Weighted betweenness centrality

Betweenness centrality (BC) is another important topological concept for exploring the robustness of urban road networks [61]. BC_i is defined at each node i, as:

$$BC_i = \sum_{j,k \in V} \frac{N_{jk}(i)}{N_{jk}} \tag{16}$$

where $N_{jk}(i)$ is the number of shortest paths passing through the node i, and N_{jk} is the total number of shortest paths between any pair of nodes.

The edge weight is the actual distance of the link so it is called weighted Betweenness centrality. Depending on the needs of each particular piece of research, however, the edge weight of betweenness centrality may use different types of values, such as flow on each link and physical distance. Since there is usually a lack of data on link flows, physical distance is generally used as the weight of links [62], and we follow this approach here.

Betweenness measures how often a given node connects a network's most critical paths; thus BC_i is the importance of that given node in those networks [63]. This helps to identify the key components and the robustness of networks subject to disruptions in specific localities.

C. Database

The novel RAI introduced above is used to assess the robustness of multi-scale URNs suffering from global capacity degradation. Data related to URNs are mainly obtained from a website[1] frequently used for transportation problems. Since the available data sources are very limited, and since it is computationally expensive to calculate UE and SO solutions for large URNs, we selected networks from Anaheim, Friedrichshian centre, Prenzlauerberg centre, Tiergarten centre, Mitte centre, and Mitte-Prenzlauerberg-Friedrichshain (MPF) centre for the benchmark analysis of the robustness. These URNs are appropriate for exhibiting how RAI effectively examines the robustness of multi-scale URNs. In this study, we mainly focus on single-mode (car) traffic, and the OD demand is assumed to be fixed. In reality, OD demand is probably uncertain and varies over time, but on the one hand, real-time OD demand data is not available from the dataset, on the other hand, the number of traffics in cities between origins and destinations tends to be stable for a relatively long term. Therefore, fixed OD demand is appropriate to be used to assess robustness here.

IV. CASE STUDY

This section applies the methodology described above to determine the robustness performance of the six selected urban road networks in the context of global capacity degradation. In the study, the size of the selected URNs is appropriate for frequently calculating total travel cost at equilibrium, and global disruptions can be defined as events that cause the capacity degradation of URNs at global level, such as extreme weather conditions. Although there are many ways to assess the robustness of a network, as explained in section 2, these are unable to quantitatively examine and compare the robustness performance of multi-scale urban road networks experiencing disruptions, taking into account travel demand, link capacity, driver behaviors and so on. Thus the relative area index (RAI) has been developed here to conduct benchmark analysis of robustness for URNs with different sizes, and then make comparisons to the results of WBC.

A. Benchmark analysis of robustness based on RAI

As can be seen from Fig. 2, it presents the relative TUE and TSO curves for the six selected networks when they are subject to global capacity deterioration. Here TUE and TSO refer to the total travel cost at UE and SO equilibrium under different levels of capacity degradation, respectively. The values of TUE and TSO are normalized by their values without any capacity reductions.

In this section, three sets of RAI are calculated using three different weighting parameters (WP), which emphasize the impact of the different types of disruptions on the network performance. The first WP takes the equal values, and is denoted as '*WP1*' in Fig. 3. As for the second and third WP, lower (higher) weight values are assigned to higher capacity degradation and higher (lower) values are assigned to lower capacity degradation, and are denoted as *WP2* and *WP3*, respectively. The values of *WP2* and *WP3* vary from 12 to 0 and 0 to 12 accordingly so as to distinguish the impact of different levels of capacity deterioration. In fact, range of values depends on the range of capacity reduction. Assigning values to these weights is an interesting research topic, but we are not going to discuss it due to the limitation of space and the scope of this study. In this study, we just simply use the percentage of network capacity reduction to indicate the impacts of global

[1] http://www.bgu.ac.il/~bargera/tntp/

disruptions on the URNs, which are all based on previous experience rather than precise calibration. As the advance of Information and Communication Technology (ICT), advanced sensors have potential to accurately estimate the global capacity degradation of URNs, which would be our focus in the future study.

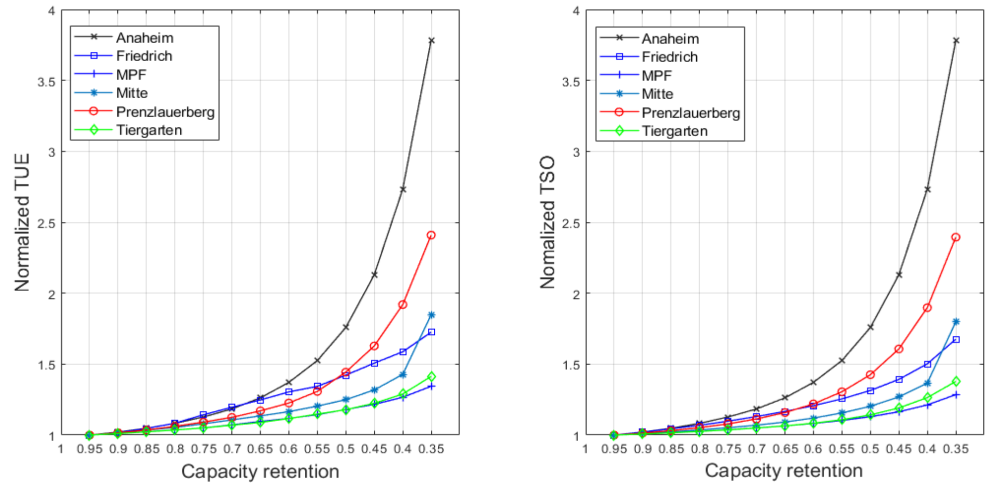

Fig. 2. Normalized TUE and TSO curves for six urban road networks subjected to a global reduction in capacity

The figure shows global capacity reduction ranges from 0% to 65% (i.e. a 100%–35% capacity retention rate). The reason why the capacity reduction is only within the range 0% to 65% is that this range is appropriate for frequent calculation of UE and SO equilibrium, and examples here are just used for presenting how this novel RAI works. This figure shows the curves of normalized total cost of UE and SO for selected URNs at different levels of global capacity degradation. It is evident from the normalized TUE and TSO data in Fig. 2 that the network whose total cost varies the most when it experiences capacity reductions is that of Anaheim. On the other hand, the MPF network is relatively close to original total cost, and curves of other networks such as Friedrichshian and Prenzlauberg, cross each other. If the WPs at each level of capacity reductions are equal (*WP1* case), we may say the robustness of Anaheim is the worst and WPF is the most robust among the six selected URNs suffering from global capacity degradation. However, it is difficult to tell which of the other URNs has better robustness since some of the curves overlap or cross. If we turn then to the *WP2* and *WP3* cases, it becomes still more difficult to distinguish the robustness. In these cases, the RAIs are calculated based on (16) so as to quantify the magnitude of deviations as accurately as possible, by taking into account the nature of different types of disruptions. All RAI values for the different types of WP are shown in Fig. 3.

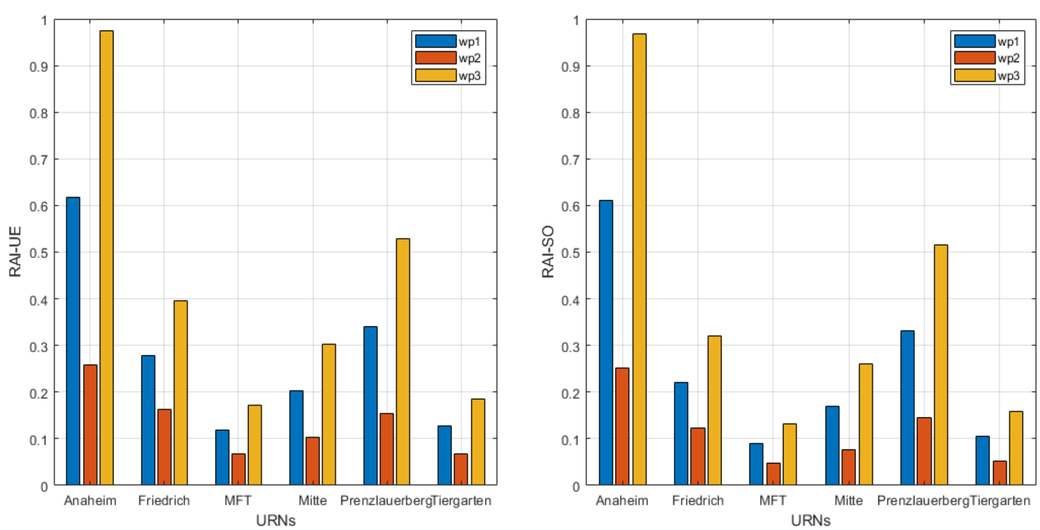

Fig. 3. RAIs of URNs based on TUE and TSO with three types of WP

As can be seen from Fig. 3, three sets of RAI for selected URNs are presented based on UE and SO principles, and the ranking based on RAI-SO is approximately consistent with that based on RAI-UE. In the principle of UE, RAIs for three types of WP show that Anaheim has the worst robustness and MFT is assessed as the most robust against the global capacity degradation from 0% to 65%. Overall, rankings of RAI in all three cases of WP are nearly identical, and in the cases of *WP1* and *WP3,* the following robust URN is Tiergarten, Mitte, Friedrichshian and Prenzlauerberg rank third, fourth and fifth robust. In the case of *WP2*, due to the fact that lower capacity degradation takes higher weight, the ranking of robustness based on RAI is slightly different from the cases of *WP1* and *WP3*, and Friedrichshian is measured as the second worst robust, followed by Prienzlauerberg, Mitte and Tiergarte.

In contrast to UE, the rankings of RAIs based on SO for all three types of WP are completely identical, MFT network shows the best robustness among all selected URNs, the following are Tiergarten, Mitte, Friedich and Prienzlauerberg, while Anaheim seems to have worst robustness against global disruptions. Due to the fact that RAI is calculated by considering many realistic characteristics, it is very difficult to distinguish which factors may impact the robustness of Anaheim most greatly, but network topology plays an important role in its robustness. The rankings between RAI-SO and RAI-UE are approximately the same except the fourth and fifth places of RAI-UE with *WP2*. In addition, all values of RAIs based on UE and SO with three types of WP are summarized in **TABLE II**, and it demonstrates that differences of robustness are not completely related to the size of URNs (number of nodes and links), that is, the immunity of URNs to global disruptions is not necessarily correlated with the scale of URNs. Intuition would suggest that the larger the scale of a URN the more robust it is likely to be, since larger URNs are likely to have more spare capacity [64]. Our finding goes against this intuition, however. The reason for this non-intuitive result depend on the complex nature of urban traffic and reflects realistic factors such as flow patterns, network topology and user behaviours.

Overall, as can be seen in **TABLE III**, different types of WPs appear to have little impacts on the ranking of robustness. Also, the rankings of RAIs under principles of UE and SO are nearly identical. However, it is worth noting that RAIs under the principle of SO are smaller than those under UE (as shown in Fig. 4), which implies that when the URNs suffer from global disruptions, global management from central entities may achieve better robustness than all individual users selfishly pursuing personal benefits maximum. In fact, the differences of RAI under UE and SO principles are very similar with Price of Anarchy [65], which is also used to measure the inefficiency of the systems caused by selfish behaviors.

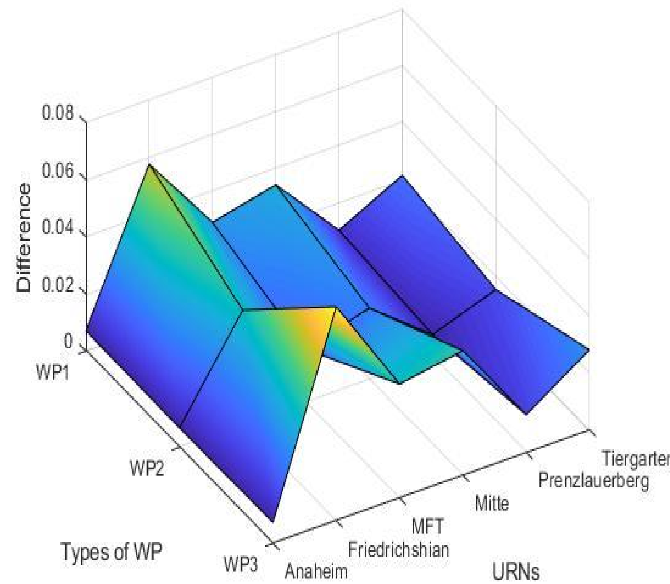

Fig. 4. Differences of RAIs between UE and SO

B. *Comparisons between RAI and WBC*

RAI-UE and RAI-SO are compared in **TABLE II** with the *WBC*, which, as explained in section 3, has been used to measure the robustness of networks [27].

As can be seen, **TABLE III** shows how these networks rank in terms of their robustness.

TABLE II
Summary of RAIs and WBC for six urban road networks (*N* denotes the number of nodes and *L* represents the number of links).

Networks	*N*	*L*	*RAI-UE*			*RAI-SO*			*WBC*
			WP1	*WP2*	*WP3*	*WP1*	*WP2*	*WP3*	
Anaheim	416	914	0.6171	0.2590	0.9752	0.6100	0.2522	0.9678	0.0316
Friedrichshian	224	523	0.2786	0.1625	0.3947	0.2211	0.1225	0.3198	0.0406
MPF	975	2184	0.1196	0.0671	0.1721	0.0905	0.0487	0.1322	0.0124
Mitte	398	871	0.2029	0.1021	0.3036	0.1686	0.0773	0.2600	0.0309
Prenzlauerberg	352	749	0.3409	0.1538	0.5280	0.3305	0.1462	0.5147	0.0364
Tiergarten	361	766	0.1266	0.0679	0.1854	0.1050	0.0525	0.1575	0.0352

TABLE III
Robustness rankings of urban road networks

Rank	*RAI-UE*			*RAI-SO*			*WBC*
	WP1	*WP2*	*WP3*	*WP1*	*WP2*	*WP3*	

1	MPF	MPF	MPF	MPF	MPF	MPF	MPF
2	Tiergarten	Tiergarten	Tiergarten	Tiergarten	Tiergarten	Tiergarten	Mitte
3	Mitte	Mitte	Mitte	Mitte	Mitte	Mitte	Anaheim
4	Friedrichshian	Prenzlauerberg	Friedrichshian	Friedrichshian	Friedrichshian	Friedrichshian	Tiergarten
5	Prenzlauerberg	Friedrichshian	Prenzlauerberg	Prenzlauerberg	Prenzlauerberg	Prenzlauerberg	Prenzlauerberg
6	Anaheim	Anaheim	Anaheim	Anaheim	Anaheim	Anaheim	Friedrichshian

The *WBC* can measure how frequently a given node of URNs can be passed by the shortest paths of all OD pairs [3]. According to [27], a network is more robust if the proportion of nodes with high *BC* is lower, which means the *WBC* of a network can be related to the robustness of the network. **TABLE III** shows a significant difference between the raking obtained using RAI-UE or RAI-SO and those obtained WBC. However, RAI-UE, RAI-SO and *WBC* all identify MPF the most robust URN. The Spearman correlation coefficients of rankings between them are not very high, and all below 0.55. Here Spearman correlation coefficient is used to measure how well the monotonic relationship between two variables exists [66]. Although betweenness centrality can measure the "importance" of a given node in a network, it does so from the perspective of network topology alone, and is thus not a sophisticated measure encompassing the characteristics that realistically inform URNs, such as capacity, flow propagation and driver behaviors. This weakness is addressed by RAI-SO and RAI-UE. The RAI also better quantifies the robustness of urban road networks experiencing global capacity degradation. Altogether, therefore, the proposed RAI offers a more complete and realistic assessment of the robustness of urban road networks. The differences of robustness among these six URNs root in distinctive network structure and spatial layout, different distributions of travel demand on different OD pairs, and non-identical travelers' behaviors. These heterogeneous characteristics jointly lead to different robustness of the URNs, and we may explore this in the future given that the current datasets are very limited.

Through such comparisons, the robustness rankings of these multi-scale URNs against global disruptions are presented and analyzed, which may shed light on the planning and management of urban traffics.

V. CONCLUSION

In the context of Health Examination (HE) of urban transportation, in order to measure the immunity of urban road networks (URNs) against disruptions which may cause the global capacity degradation, this study proposed a novel index, the relative area index (RAI), that quantitatively measures robustness and allows to conduct, for the first time, robustness benchmarking amongst URNs with different sizes. This research sheds light on how to quantify the immunity of urban transportation against global disruptions. The proposed RAI provides different insights from distinct perspective to assess the robustness of multi-scale URNs, and compared to WBC, this RAI is more confident to provide more reliable and realistic suggestions regarding mitigation of disruptions to the planners and managers of urban transportation.

In the future, this research could be further developed in a variety of ways. Firstly, due to the limitation of data sources, only six URNs are utilized as numerical examples. The robustness of many more URNs with different characteristics can be calculated with our RAI. Following this, other aspects of the immunity of urban transportation can be explored and quantified, such as the local disruptions which may cause node/link capacity reductions. Furthermore, although this study provides an effective tool for measuring the robustness and conducting benchmark analysis of multi-scale URNs, the reasons why some URNs show better robustness than others based on RAI are not deeply explored, and many factors are probably involved, such as travel demand, flow patterns and topology of URNs.

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