



Assessing the Environmental Aspects of Road Network Resiliency

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Abstract

Evaluating road networks' performance during and after a disruption and/or malfunction is of great importance. The performance of the road networks includes four concepts: reliability, vulnerability, robustness, and resilience. Among these concepts, the concept of resilience, which evaluates the road network's performance after a disruption/malfunction, is very significant. On the other hand, given that the road network is one of the primary sources of air pollution and plays a crucial role in urban sustainability, the amount of polluted emission should be considered in road network performance (resilience) analysis. The literature presents several measures such as travel time, queue length, recovery time, network's total cost, etc., to study road network resiliency. A review of previous studies demonstrates that the number of studies that considered environmental aspects in road network resiliency evaluation is scarce. Therefore, in this study, new network resilience measures that consider environmental factors are presented. These new measures show how the amount of polluted emission will change when a disruption occurs in the road network. After introducing and defining these new environmental resiliency measures, the Sioux Falls road network is simulated as the case study in Aimsun. The Sioux Falls road network (based on new resiliency measures) is evaluated when the speed of links (sections) is reduced randomly. The London Emission Model (LEM) is used for estimating the amount of polluted emission.

Keywords

Road network resiliency • Urban sustainability • Polluted emission • Traffic simulation • Environmental aspects • Aimsun

1 Introduction

Evaluation of transportation network performance under incident or disruption/malfunction conditions is of great importance. The transportation network's performance includes four concepts: reliability, vulnerability, robustness, and resilience (Calvert & Snelder, 2018). These concepts are very close to each other in such a way that reliability, vulnerability, and robustness are mentioned as resilience characteristics in previous studies (El Rashidy, 2014). The concept of resilience has attracted widespread interest in the last few years. This concept was born in the field of ecology and, at its origin, it was identified with an ecological system's resistance to change (MacArthur, 1955). Later on, it has found application in economics (Rose & Krausmann, 2013), engineering (Bruneau et al., 2003), and, lastly, transportation engineering (McDaniels et al., 2008).

Although resiliency concepts have been evolved for many years (since the 1950s), many researchers concluded that there is no unified definition of resiliency. So that, each researcher has given a specific definition to resilience according to the objectives of their project and the type of infrastructure being studied (Gauthier et al., 2018; Lhomme et al., 2013). Therefore, according to the objectives, resiliency in transportation systems is taken into concern in this article.

Resiliency in transportation systems is defined as "The ability to prepare for changing conditions and withstand, respond to, and recover rapidly from disruptions." (Scope, 2015). There are two types of incident or disruption (that leads to changing conditions) in the transportation system:

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(1) natural disaster (2) abnormal conditions. Natural disasters include earthquakes, floods, adverse weather conditions, etc., and result in network-wide failures. Usually, natural disaster leads to speed and capacity reduction at the network level. While abnormal conditions such as road maintenance sites, accidents, malfunction, etc., result in a road closure of specific links (Mehrabani et al., 2021). Usually, abnormal conditions occur in two ways: (1) incidents (for example, accident, road maintenance sites, man-made disasters); (2) road assets' malfunction, which leads to speed/capacity reduction (for example, pavement cracks). This article examines the road network's resiliency in abnormal conditions, which leads to speed/capacity reduction.

2 Literature Review

There are four different methods for the resiliency analysis of transportation networks: (1) topological models of resiliency (Gauthier et al., 2018; Lhomme et al., 2013; Zhang et al., 2015) (2) optimization models of resiliency (Kaviani et al., 2017; Omer et al., 2013; Patil & Bhavathrathan, 2016) (3) big data analysis (Liu & Song, 2020; Tympakianaki et al., 2018) (4) operational and simulation models of resiliency (Aghababaei et al., 2020; Bala et al., 2019; Ganin et al., 2017; Kamga et al., 2011; Sgambi et al., 2020). In what follows, some studies in each of the above groups are examined.

One of the studies using topological models for analyzing resiliency in natural disaster (flood) conditions is Lhomme et al., (2013). This study used Geographic Information System (GIS) to achieve network topological features. Using resistance capacity, absorption capacity, and recovery capacity, a new redundancy measure is defined. Zhang et al. (2015) evaluate the resiliency of various road network structures. The authors argue that different network structures (e.g., grid network, ring network, etc.) have different resiliency levels. Average degree and cyclicity metrics are used to indicate the redundancy level of the road network. The results suggest that the redundancies level and the resilience level have a direct relationship with each other. Another view of topological models of resiliency is presented in the study of Gauthier et al., (2018). The difference between this study and other topological models is that the traffic demand distribution and the road traffic dynamics are considered. This study concluded that various resiliency metrics lead to different importance levels for the network's links. The topological models of resiliency are able to analyze any system and require little time for their implementation. However, they are inefficient since they cannot capture the network's specific characteristics compared to other approaches (Sgambi et al., 2020).

The number of studies in which optimization models of resiliency are presented is less than the other approaches. One of these studies is the study of Omer et al., (2013). The model of this study tried to minimize the network travel time. This study used three measures for road network resiliency: (1) cost resiliency, (2) environmental resiliency, and (3) travel time resiliency. The environmental resiliency is captured by producing the CO₂ emission per fuel and the fuel consumed in the whole network. Although this study is among a few studies which consider environmental issues, the emission model (used for calculating the environmental resiliency measure) is at the macroscopic level, which does not account for vehicles characteristics in pollutant emission. A similar optimization model was reported by Patil and Bhavathrathan (2016). The transportation network's resiliency is evaluated using travel time optimization and different road network measures. This study presented a generalized index of resiliency using network cost. Besides, Kaviani et al. (2017) introduce a bi-level optimization model. This model finds the optimal location of guidance devices through the whole road network. The optimization model tries to minimize total travel time, which is an essential measure for road network resiliency. This paper's outcomes indicate that when the proposed optimization model optimizes roadside guidance devices' location, the recovery phase time is less than the usual condition.

Although topological and optimization methods of road network resiliency can be applied to any graph modeling, the following drawbacks still exist in these studies (Gauthier et al., 2018; Liu & Song, 2020): (1) they are usually demand-insensitive (2) less attention has been paid to recovery simulation (3) although, after a disaster, the entire capacity of a network does not get affected, these studies usually consider the complete removal of nodes or links. (4) different traffic modes cannot be viewed in graph theory, and (5) the specific characteristics of one system in relation to another are overlooked.

The studies that implement big data analysis for evaluating resiliency compare the traffic data before and after a disruption. For instance, Tympakianaki et al., (2018) employed link sensor counts, automated vehicle location, automated passenger count, automated fare collection, automated number plate recognition, taxi floating car data, and google floating car data to assess the effect of tunnel closure on multimodal transport. The results indicate that travel times are higher on closure days than on other days. This approach's disadvantage is that it requires a considerable amount of data; therefore, this approach is inefficient when no data is available.

In Kamga et al.'s (2011) study, the Chicago road network is simulated in incident conditions using VISTA software with a dynamic traffic assignment method. Network-wide

total travel time is employed as a network performance measure. The results demonstrate that incidents affect both the incident location and the entire road network simultaneously (network-wide effects). Besides, the authors pointed out that the availability of information on the presence of incidence could help the incident management process. Ganin et al.'s (2017) study extracted the topological features from OpenStreetMap (OSM) data. This study's transportation model (a gravity-like model) uses the population of each zone, distances between zones, and distance factors as input and presents the flow between each origin–destination pair (origin–destination matrix) as output. Extra delays caused by 5% link disruption are employed as road network resiliency measures. The results show that many inefficient road links in normal conditions are resilient in an abnormal state. In contrast, some efficient links (in normal conditions) are not resilient in an abnormal conditions. This circumstance indicates the resiliency and the efficiency of the road network should be examined separately. Balal et al. (2019) aimed to compare different resiliency measures and employed the DynusT traffic simulator. The candidate resiliency measures in this study are detour road delay, upstream road delay, segment travel time, segment speed, and queue length. The finding of this study demonstrates that different resilience measures lead to different resiliency and efficiency levels of importance for links. Therefore, they recommend that each researcher should consider their measures based on their project objective. Using Aimsun mesoscopic simulator, Aghababaei et al., (2020) evaluate the New Zealand road network's performance after a natural disaster (earthquake). This study is one of the few studies that has examined the road network's performance at the country level (New Zealand). However, it should be pointed out that this study only considered the state highways and did not consider the main roads. Evaluated measures in this study include density, delay time, total traveled distance, travel time, traffic flow, and traffic count. The operational and simulation models of resiliency (used as the modeling approach in the current study) require much more work than topological models for their realization. However, they are more effective in analyzing network behavior (Sgambi et al., 2020).

On the one hand, the literature review demonstrates that many measures such as travel time, queue length, emission, time of recovery, peak distribution, network total cost, etc., (Murray-Tuite, 2006; Shang, 2016) have been employed as network performance and resiliency measures. Besides, some studies introduce new measures such as new redundancy indicators (Lhomme et al., 2013), generalized index of resilience (Patil & Bhavathathan, 2016), and general link performance indicator for resilience (Calvert & Sneldera, 2018). Evaluating these measures suggests that most of the presented measures are based on capacity, delay, travel time, and network cost (traffic-related measures) (Balal et al.,

2019; Kaviani et al., 2017; Murray-Tuite, 2006; Shang, 2016).

On the other hand, the transport sector accounts for 25% of greenhouse gas emissions, which is continuing to rise (Mehrabani et al., 2021). Besides, in previous studies, it has been stated that environmental issues are one of the principles of infrastructures' resiliency (Twumasi-Boakye & Sobanjo, 2018). However, despite the importance of environmental issues, fewer studies have considered environmental issues to measure network resiliency (Omer et al., 2013; Shang, 2016). Therefore, in this study, in addition to the existing road network resiliency measures, network resiliency measures in which environmental issues are taken into account have been studied. To achieve this goal, vehicle-based simulation (VBS) is used in the Aimsun environment.

In what follows, the network resiliency measures that have been examined in this study are introduced (Sect. 3). Then, in Sect. 4, the modeling process in Aimsun with some explanations about the case study will be presented. In Sect. 5, modeling outcomes are given. Finally, in Sect. 6, recommendations and suggestions for future studies are expressed.

3 Road Network Resiliency Measures

Road network resiliency measures can be grouped into three categories (Sun et al., 2018). The first group compares the functionality (loss) before and after a disruption. These measures are either traffic-related (travel time, throughput, capacity, etc.) or topology-based (e.g., connectivity and centrality). The second group uses measures that cover the recovery process after a malfunction. The second group's measures are usually calculated using the resilience triangle. The third group uses resilience measures to quantify an event's impact on society and the economy (environmental). In this study, four resiliency measures are considered, two of which are traffic-related and the two others are environmental-related.

3.1 Travel Time Resiliency

This measure compares normal conditions' travel time (for the entire network) with abnormal conditions' travel time. This measure's value is obtained by dividing the travel time in abnormal conditions (capacity or speed reduction in the network) by the travel time in normal conditions. Travel time resiliency is calculated by Eq. (1).

$$R_T = \frac{\text{Travel time (in abnormal condition)}}{\text{Travel time (in normal condition)}} \quad (1)$$

In normal conditions (without a disruption), the travel time resiliency is equal to 1. A disruptive event raises travel time between two nodes. Therefore, the resiliency approaches values greater than 1. The more the value is near to 1, the more resilient the network is.

3.2 Mean Speed Resiliency

This measure compares the network mean speed before and after a disruptive event, given by Eq. (2).

$$R_S = \frac{\text{Mean Speed (in normal condition)}}{\text{Mean Speed (in abnormal condition)}} \quad (2)$$

When an abnormal condition occurs in the network, the vehicles' speed usually decreases, so the higher the intensity of the abnormal condition in the network, the greater this measure's value. The more the value is near to 1, the more resilient the network is.

3.3 Environmental Resiliency

Environmental issues are one of the issues that have attracted much attention in recent years. After disruptive events in road networks, the vehicles' speed usually reduces, which is caused by capacity reduction. This speed reduction across the road network increases vehicle emissions. Therefore, in this study, the following measures are defined to examine whether the road network is environmentally resilient or not.

$$R_{E1} = \frac{\text{Emitted NO}_x \text{ (in abnormal condition)}}{\text{Emitted NO}_x \text{ (in normal condition)}} \quad (3)$$

$$R_{E2} = \frac{\text{Emitted CO}_2 \text{ (in abnormal condition)}}{\text{Emitted CO}_2 \text{ (in normal condition)}} \quad (4)$$

In this study, environmental resiliency is investigated by how the amount of polluted emission (by vehicles) changes before and after abnormal conditions. The amount of emitted pollution by vehicles is calculated using the London Emission Model (LEM), a mesoscopic traffic emission model. Please refer to Aimsun User's manual (2018) for more information about this model. It should be noted that the LEM is already embedded in Aimsun.

4 Traffic Simulation

The Sioux Falls road network is simulated in the Aimsun environment. The first step of traffic simulation is to import road network data (supply data) into the Aimsun. To do so, Sioux Falls road network information is extracted from

Table 1 Road network information

Type of road	Speed (km/hr)	Capacity (pcu/hr/ln)
Motorway	120	2500
Primary	100	2300
Secondary	90	2100
Tertiary	80	2000

OpenStreetMap. A code was implemented in the Overpass-Turbo environment to extract some specific types of roads. The types of roads extracted from OpenStreetMap and their features are illustrated in Table 1.

The demand data (origin–destination matrix) is extracted from Leblanc et al.'s (1975) study, presenting 76 links and 24 nodes for the Sioux Falls road network. The origin–destination matrix is given in hundreds of vehicles per day. Therefore, the peak hour demand matrix is extracted using daily volume distribution (NCHRP, 2004). Finally, the morning peak hour (7:00–8:00) is simulated with 24 nodes and more than 2000 links (section) in Aimsun. The simulated network in the present study and the Sioux Falls graph (Leblanc et al., 1975) are shown in Fig. 1.

As mentioned earlier, the objective of the current paper is the network resiliency investigation under abnormal conditions. These abnormal conditions can be due to incidents such as car accidents or pavement failures. Therefore, it is clear that these abnormal conditions occur randomly in different road sections, and it is not possible to determine the place of speed reduction. As a result, in this study, ten speed reduction scenarios are considered for simulation. In the first scenario, the speed of 10% of the sections is reduced by 50%. In the second scenario, the speed of 20% of the sections is reduced by 50%. This process is done for 30, 40, ..., 100% of sections. The candidate sections for speed reduction are chosen randomly using Aimsun scripting. The scenarios examined in this paper are given in Table 2. Since the size of the studied network in this study (Sioux Falls network) is on a city scale, microscopic simulation is very time-consuming. Therefore, mesoscopic simulation has been used. The traffic assignment method used in this simulation is dynamic user equilibrium (DUE) (Which considers 20 iterations for convergence).

5 Results

Ten scenarios were simulated in Aimsun, and for each of these scenarios, the values of road network resiliency measures (introduced in Sect. 3) were calculated. Simulation results and the calculated values of road network resiliency measures are given in Table 3. For better evaluation of the simulation results, the values of these measures are illustrated in Figs. 2, 3, 4, and 5.

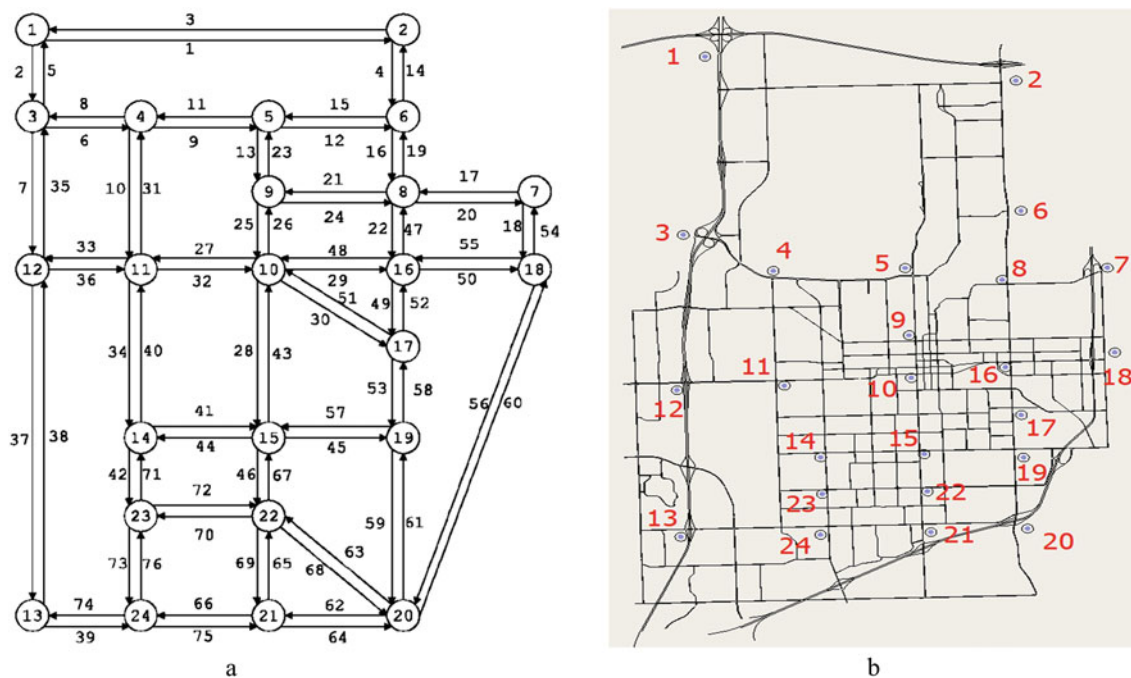


Fig. 1 a Sioux falls network by Leblanc et al. (1975), b Sioux falls simulated network in Aimsun (present study)

Table 2 Simulation scenarios

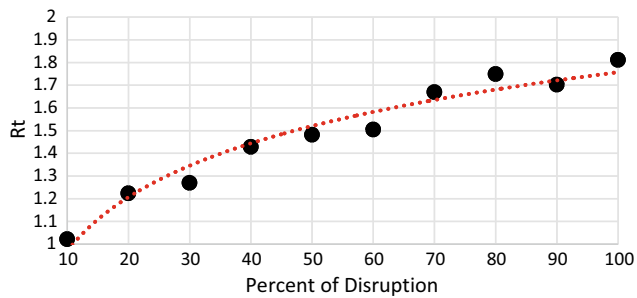
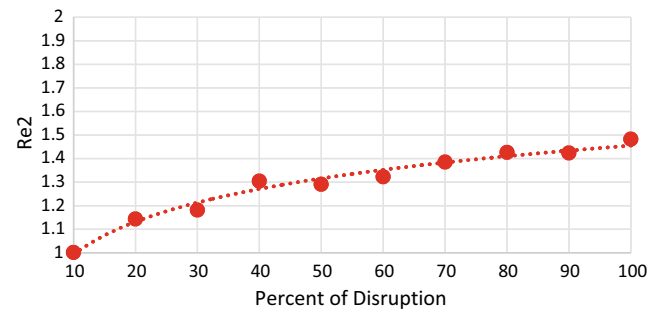
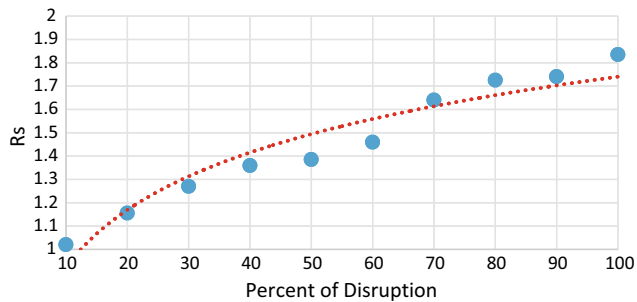
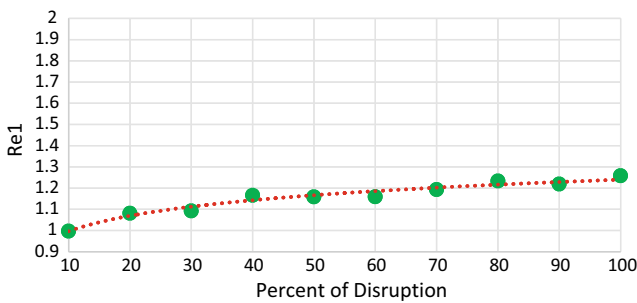
No.	Speed reduction amount (%)	Section selection criteria	Percentage of sections in which speed reduction occurs (Percent of disruption)
1	50	Randomly	10
2			20
3			30
4			40
5			50
6			60
7			70
8			80
9			90
10			100

Figure 2 shows the values of the travel time resiliency measure (R_T). The line graph shows the value of R_T from 1 to 2 on the Y-axis against the percentage of disruption from 10 to 100 on the X-axis. As the percent of disruption increases, the value of R_T increases. In other words, there is a direct relationship between the number of sections affected by speed reduction and network travel time. Consequently, road network resiliency decreases with the increase in the number of section in which the speed is reduced. As can be seen, the variation rate in travel time resiliency changes nonlinearly. The rate of change in low and medium percentages of disruption (10–70) is very high, but it gets lower when we get closer to the end of the graph (percent of disruption 70–100). Therefore, it can be concluded that the

network is less sensitive to speed reduction beyond the percent of disruption 70% (the breakpoint). This figure also shows that if the whole network’s speed decreases by 50%, the total travel time will be less than doubled ($R_T = 1.8$). The mean speed resiliency measure is another measure studied in this paper. The values of this measure are shown in Fig. 3. As can be seen, with a 50% reduction in speed in all sections (scenario 10), the average speed in the entire network is increased by 80% ($R_S = 1.8$). Comparison of this measure with travel time resiliency measure (Fig. 2 versus Fig. 3) shows that the behavior of these two measures is very similar to each other. This circumstance is because speed and travel time have a direct relationship with each other.

Table 3 Simulation results

No	Percent of disruption	R_T	R_S	R_{E1}	R_{E2}
1	10	1.022	1.020	0.997	1.001
2	20	1.224	1.156	1.081	1.143
3	30	1.270	1.270	1.092	1.181
4	40	1.428	1.359	1.166	1.304
5	50	1.482	1.386	1.159	1.291
6	60	1.505	1.460	1.159	1.323
7	70	1.670	1.640	1.193	1.385
8	80	1.749	1.725	1.233	1.426
9	90	1.702	1.741	1.219	1.423
10	100	1.812	1.835	1.259	1.482

**Fig. 2** Travel time resiliency measure in different scenarios**Fig. 5** Environmental resiliency measure (R_{E2}) in different scenarios**Fig. 3** Mean speed resiliency measure in different scenarios**Fig. 4** Environmental resiliency measure (R_{E1}) in different scenarios

The last measures examined in this study are the ones related to environmental resiliency (R_{E1} and R_{E2}) for comparison of emitted pollutants under normal and abnormal conditions. The R_{E1} is used for the emission of NOx, and the R_{E2} is defined for the amount of emitted CO₂. These measures are illustrated in Fig. 4 and Fig. 5, respectively. Examining these measures also shows that the amount of emitted NOx and CO₂ by vehicles increases with the percentage of disruption in the sections. So that if the speed of all sections is reduced by 50%, the amount of polluted emission will be approximately 1.5 times ($R_{E1} = 1.259$; $R_{E2} = 1.482$). It can be concluded that the amount of polluted emission by vehicles in abnormal conditions increases significantly. Therefore, environmental-related measures are highly important among traditional road network resiliency measures and should be considered in the decision-making process and evaluating road network performance. However, it should be noted that the rates of changes in environmental-related measures are lower than those of traffic-related measures. In other words, the network is less sensitive to emitted pollution than travel time and speed.

To compare the above measures better (R_T , R_S , R_{E1} , R_{E2}), the correlation matrix of these measures is shown in Table 4.

Table 4 Correlation matrix of resiliency measures

	R_T	R_S	R_{E1}	R_{E2}
R_T	1	0.988**	0.987**	0.991**
R_S	0.988**	1	0.965**	0.973**
R_{E1}	0.987**	0.965**	1	0.996**
R_{E2}	0.991**	0.973**	0.996**	1

**Correlation is statistically significant at 0.01 level

As can be seen, these four measures have a significant correlation with each other, which indicates that the disruption scenarios have almost the same effect on increasing travel time/emission and decreasing average speed. However, the rates of change are not the same. The rate of changes in R_T and R_S are very close to each other, while R_{E1} and R_{E2} has a lower rate of change in disruption scenarios.

6 Conclusion

The study of network resiliency in speed or capacity reduction scenarios (caused by natural disasters (e.g., earthquakes, floods, etc.) or abnormal conditions (e.g., vehicle accident, road maintenance sites, etc.)) is one of the issues that has attracted the attention of many researchers in recent years. Previous studies have introduced many measures for examining road network resiliency. Most of which are formed on traffic-related criteria (e.g., travel time, delay, etc.). A critical issue that has been overlooked in previous studies is the study of environmental issues in road network resiliency.

Therefore, in this study, four road network resilience measures were introduced, two of which are calculated using the total travel time and the average speed in the whole network (traffic-related measures). The other measures are based on polluted emissions by vehicles (NOx and CO₂). In the simulated scenarios, the speed decreases by 50% in a certain percentage of sections (which are selected randomly). For each scenario, the values of the above measures were calculated. These measures' values showed that the higher the percentage of speed deceleration in the sections (percent of disruption), the lower the network resiliency is.

The introduction of new network environmental resiliency measures showed that vehicles' amount of polluted emission increases under abnormal conditions. Although the four measures of R_T , R_S , R_{E1} , and R_{E2} , have almost the same behavior, the rates of change (when the network is in abnormal conditions) for the environmental-related measures (R_{E1} and R_{E2}) are less than those of the traffic-related measures (R_T and R_S).

Examining the resiliency measures' values shows that these measures vary nonlinearly in different failure

scenarios. A noteworthy point that can be concluded from the measures' values is that the rates of change of the measures in low and medium percentages of disruption (10–70) are higher than high percentages of disruption (70–100). The results propose a nonlinear relationship between the percent of disruption and resiliency measures up to a breakpoint (percent of disruption = 70%). Beyond the breakpoint (percent of disruption = 70%), the changes' rates are meager and almost linear. This clarifies the need to present a nonlinear relationship between the percent of disruption and network resiliency measures in future studies. Besides, different traffic demand levels should be evaluated as the breakpoint is related to traffic demand.

Therefore, environmental-related indicators should be considered in the network resiliency studies and decision-making by decision-makers and policymakers. It can be concluded that a resilience network is a network in which not only traffic-related measures are considered but also other measures, including environmental-related ones, are taken into account. Moreover, the evaluation of these measures showed that they have a significant correlation. Therefore, future studies can focus on defining an indicator by combining the measures introduced in this study.

In the current study, the sections in which the speed reduction occurs were selected randomly, so it is suggested that the effect of speed reduction in pre-selected sections can be examined in future studies. So, the importance of each section and, consequently, the most critical sections can be specified. Also, this study considered a 50% reduction in speed. Other percentages of speed reduction should also be considered.

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