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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.

To study the road networks' resilience, several measures such as travel time, queue length, time of recovery, network's total cost, etc. have been presented in previous studies. 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 behavior of Sioux Falls road network (based on new resiliency measures) is evaluated when speed of links (sections) are 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

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 and 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 interests in recent years. The concept of resilience was born in the field of ecology. At its origin, this concept was identified with an ecological system's resistance to change (MacArthur, 1955). The concept of resilience has later found applications in the field of economics (Rose and Krausmann, 2013), engineering (Bruneau et al., 2003), and, lastly, transportation engineering (McDaniels et al., 2008).

Although the concept of resilience has been evolved since the 1950s, many researchers have 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 (Lhomme et al., 2013; Gauthier et al., 2018). Therefore, according to the objectives, resiliency in transportation systems is taken into concern in this article.

The 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: 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 a decrease in capacity and speed of links at the network level. While abnormal conditions such as road maintenance sites, accidents, malfunction, etc., result in a road closure of specific links (Bamdad Mehrabani et al., 2020). 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). In this article, the road network's resiliency in abnormal conditions, which leads to speed/capacity reduction, is examined.

2. Literature review

There are four different methods for the resiliency analysis of transportation networks: 1- Topological Models of Resiliency (Lhomme et al., 2013; Zhang et al., 2015; Gauthier et al., 2018) 2- Optimization Models of resiliency (Omer et al., 2013; Patil and Bhavathrathan, 2016; Kaviani et al., 2017) 3- Big Data Analysis (Tympakianaki et al., 2018; Liu and Song, 2020) 4- Operational and Simulation models of resiliency (Kamga et al., 2011; Ganin et al., 2017; Bala et al., 2019; Sgambi et al., 2020; Aghababaei et al., 2020). In what follows, some studies in each of the above groups are examined.

One of the studies that use topological models for analyzing resiliency in natural disaster (flood) conditions is Lhomme et al. (2013) study. 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. The study of Zhang et al. (2015) evaluates the resiliency of 17 different network structures. The authors argue that different network structures (e.g., grid network, ring network, etc.) have different resiliency level. The results indicate that the more redundancies built into the network (indicated by average degree and cyclicity metrics), the higher the resilience level. Another view of topological models of resiliency is presented in the study of Gauthler et al. (2018). The difference between this study and other topological models is that the dynamic properties of road traffic and the day to day distributions of traffic demand are taken into account. This study concluded that using different resiliency measures leads to different results for the degree of importance of each link. 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 network optimization problem is to minimize the average travel time. The three identified measures for road networks used in this study are the travel time resiliency, environmental resiliency, and cost resiliency. Omer et al. defined the environmental resiliency based on the environmental impact resulting from the increased level of CO_2 emissions due to delay. Environment resiliency is measured as the product of CO_2 emissions per gallon and the gallons consumed during the trip. 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 roadside guidance devices across a regional road network for improving total travel time (which is an essential measure for road network). This paper's outcomes indicate that the locating optimization model leads to a more resilient road network in which the post-disaster travel time of the network during the recovery phase is less than when no action is taken.

Although topological and optimization methods of road network resiliency can be applied to any graph modeling, the following drawbacks still exist in these studies (Liu and Song, 2020; 8. Gauthier et al., 2018): 1- They are usually demand-insensitive 2- Less attention has been paid to recovery simulation 3- Although Roads often maintain a certain traffic capacity after a hazard, these studies usually consider the complete removal of nodes or links. 4- Different traffic modes cannot be considered 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 usually compare the traffic data before and after a disruption. For instance, Tympakianaki et al. (2018) employed link sensor counts, automatic vehicle location, automatic passenger count, automated fare collection, automatic number plate recognition, taxi floating car data, and google floating car data to evaluate the multimodal effects of tunnel closure in Stockholm. The results indicate that higher travel times and lower speeds are observed on closure days than regular 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 the study of Kamga et al. (2011) the Chicago's road network is simulated in incident conditions using Visual Interactive System for Transport Algorithms (VISTA) software with a dynamic traffic assignment method. Network-wide total travel time is employed as the measure of network performance. The results demonstrate that incidents not only affect vehicles originating upstream or traversing the incident location, but also affect the whole network (network-wide effects). Besides, the authors pointed out that the availability of information on the incident presence could considerably assist in improving incident management practices. In the study of Ganin et al. (2017), the topological features are extracted from Open Street Map (OSM) data. This study's transportation model (which is 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. Traffic zones and roads are simulated as nodes and links, respectively. Additional delays due to 5% link disruption are employed as road network resiliency measure. The results demonstrate that many urban road systems that operate inefficiently under normal conditions are nevertheless resilient to disruption, whereas some more efficient zones are more fragile. This circumstance indicates the importance of examining network resilience rather than network efficiency separately. Balal et al. (2019) aimed to compare different resiliency measures and employed the DynusT traffic simulator. The candidate measures of resiliency in this study are queue length, segment speed, segment travel time, frontage road delay, and detour route delay. The finding of this study demonstrates that using different resilience measures will lead to different conclusions in the order of disruption caused by the link closures. Therefore, they recommend that each researcher should consider their own 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 average count data, average flow, total travel time, travel time, the sum of total traveled distance, the sum of delay time, and average density. 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 one hand, a review of the literature demonstrates 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 and Bhavathrathan 2016), and general link performance indicator for resilience (Calverta and 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) (Murray-Tuite, 2006; Shang 2016; Kaviani et al., 2017; Balal et al., 2019).

On the other hand, transport accounts for a quarter of greenhouse gas emissions, a figure that continues to rise as demand grows (Bamdad Mehrabani et al., 2020). Besides, in previous studies, it has been stated that environmental issues are one of the principles of infrastructures' resiliency (Twumasi-Boakye and 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 (section 3). Then, in section 4, the modeling process in Aimsun with some explanations about the case study will be presented.

In section 5, modeling results are presented. Finally, in section6, conclusions 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 directly compares the functionality measures before and after the event. These functionality measures are either traffic-related (travel time, throughput, capacity, etc.) or topology-based (e.g., connectivity, centrality). The second group uses functionality-based resilience measures that cover the functionality recovery process. The second group's measures are usually calculated using the resilience triangle. The third group uses resilience measures that can 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 whole 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 condition. Equation 1 is used to calculate travel time resiliency.

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

Under normal operating conditions, the travel time resiliency has a value of 1. A disruptive event may increase travel time between two nodes, hence making the resiliency value approach values greater than 1. The more the value is near to 1, the more resilience the network is.

3.2. Mean speed resiliency

This measure compares the network mean speed before and after a disruptive event and is given by equation 2.

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

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 the value of this measure is. The more the value is near to 1, the more resilience the network is.

3.3. Environmental resiliency

Environmental issues are one of the issues that have attracted much attention in recent years. After the occurrence of a disruptive event/abnormal condition in the road network, 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 resilience or not.

$$R_{E1} = \frac{Emitted\ NOx\ (in\ abnormal\ condistion\ )}{Emitted\ NOx\ (in\ normal\ condition)} \quad (3)$$

$$R_{E2} = \frac{Emitted\ CO2\ (in\ abnormal\ condistion)}{Emitted\ CO2\ (in\ normal\ condition)} \quad (4)$$

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

In this study, the Sioux Falls road network is examined as the case study. The first step of traffic simulation is to import road network data (supply data) into the Aimsun environment. To do so, Sioux Falls road network information is extracted from Open Street Map. A code was implemented in the Overpass-Turbo environment in order to extract some specific types of roads. The types of roads that are extracted from Open Street Map in addition to their features are illustrated in table 1.

Table 1. Road Netwrok Information

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

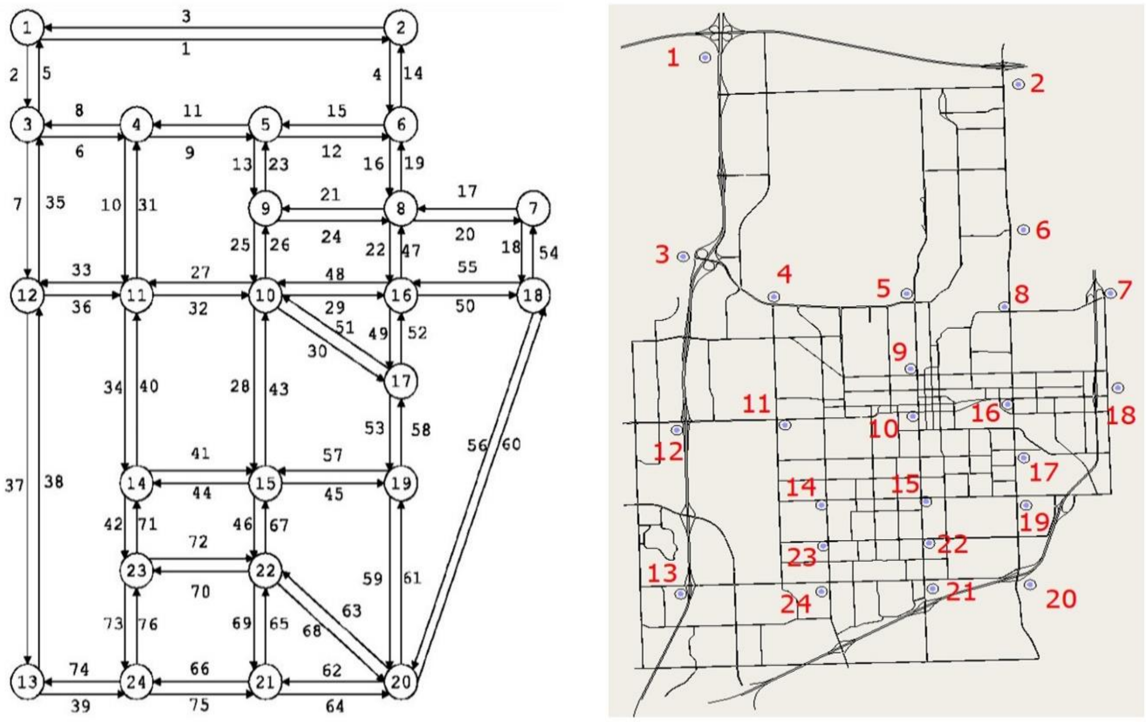
The demand data (Origin-Destination matrix) is extracted from Leblanc et al. (1975) study. In Leblanc et al. (1975), there are 24 nodes and 76 links (using graph theory). The Origin-Destination matrix is given in hundred of vehicles per day. Therefore, the peak hour demand matrix is extracted using daily 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 figure 1.

As mentioned in the introduction, the purpose of this study is to investigate network resiliency 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 sections of the road, and it is not possible to determine the place of speed reduction. As a result, in this study, 10 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.

Due to the fact that 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 (that were introduced in Section 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 Figures 2 to 5.



a b

Figure 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). Line graph shows the value of R_T from 1 to 2 on the Y-axis against 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, as the number of sections affected by speed reduction increases, the travel time of the network increases and, consequently, the value of road network resiliency decreases. As can be seen, the rate of change in travel time resiliency changes nonlinearly. The rate of change in low percentages of disruption (10 to 70) is very high, but the closer we get to the end of the graph (percent of disruption 70-100), the lower the changes' rates. Therefore, it can be concluded that beyond the percent of disruption 70% (the breakpoint), the network is less sensitive to speed reduction. 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 study. The values of this measure are shown in Figure 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 (Figures 2 vs. figure 3) shows that the behavior of these two measures is very similar to each other. This circumstance is because the speed and travel time has 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

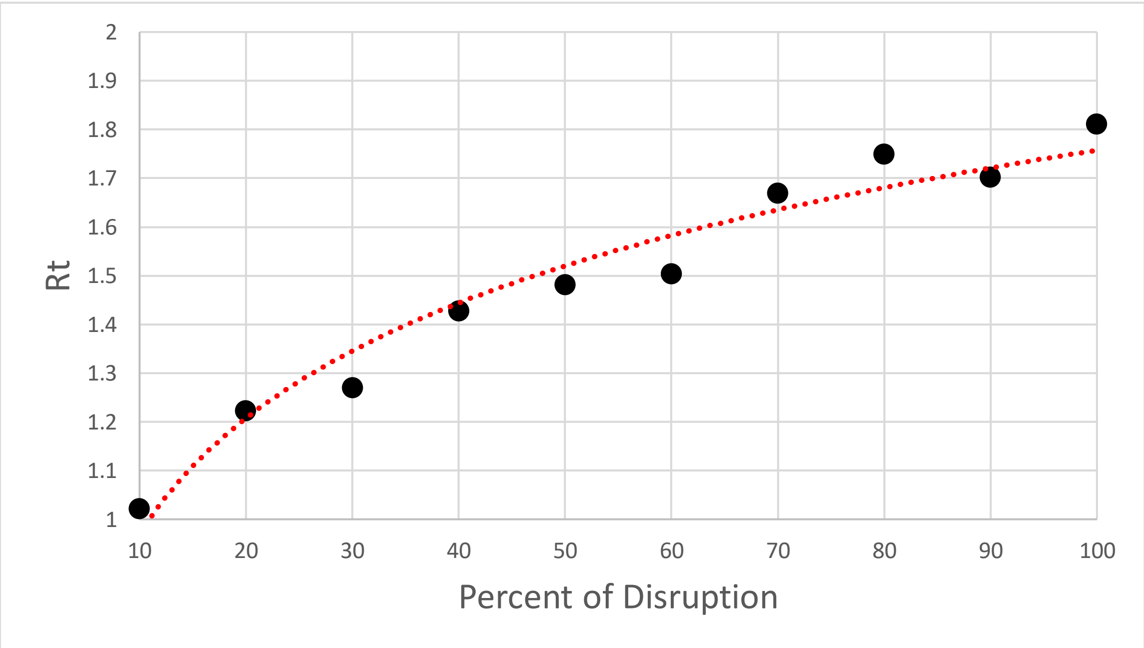


Figure 2 Travel time resiliency measure in different scenarios

The last measures examined in this study are the ones related to environmental resiliency (R_{E1} and R_{E2}). The R_{E1}, which compares the amount of emitted NOx by vehicles under normal conditions with abnormal conditions, and the R_{E2}, which compares the amount of emitted CO2 by vehicles under normal conditions with abnormal conditions, are shown in Figure 4 and Figure 5, respectively. Examining these measures also shows that the higher the percentage of disruption in the sections, the higher the amount of emitted NOx and CO2 by vehicles. 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 of high importance 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.

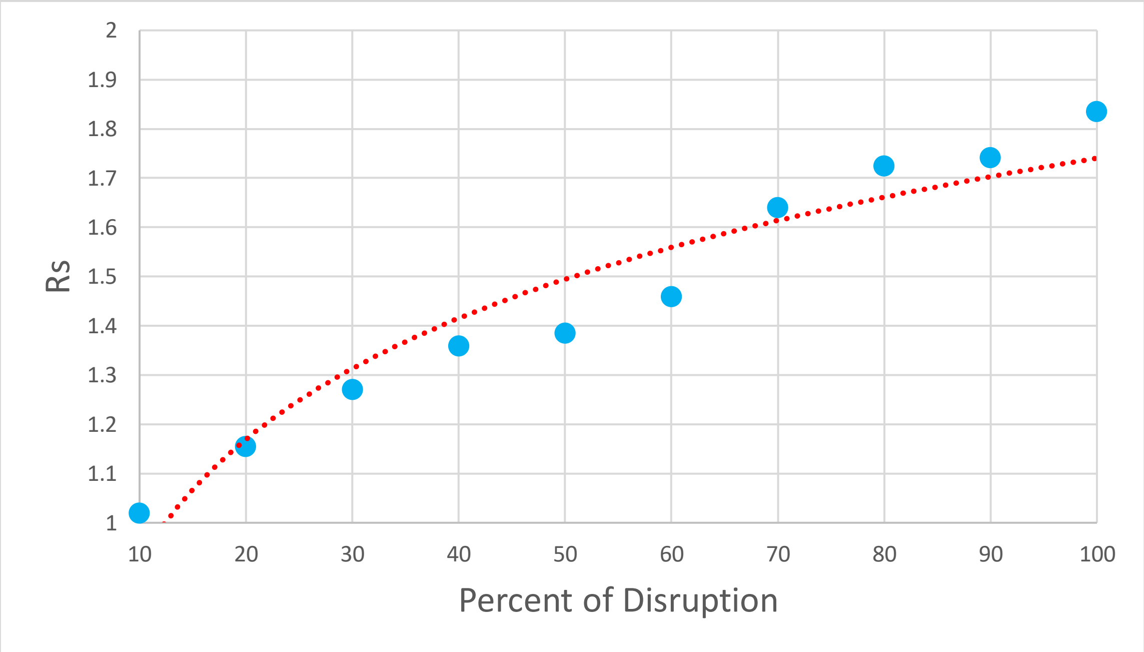


Figure 3 Mean speed resiliency measure in different scenarios

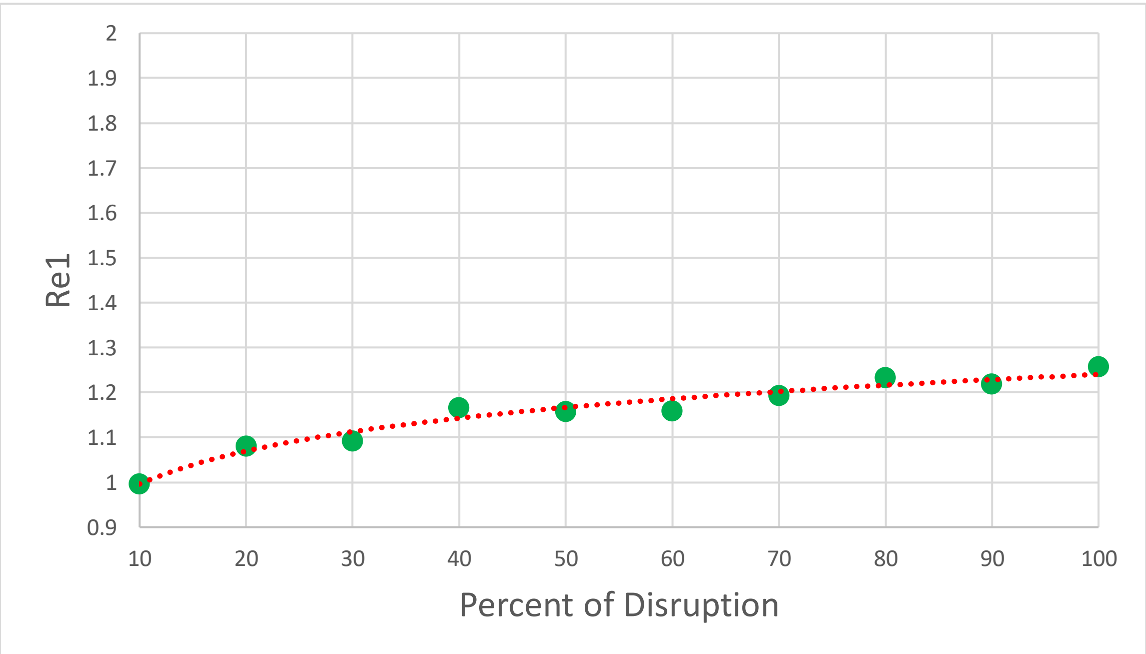


Figure 4 Environmental resiliency measure (Re1) in different scenarios

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. 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.

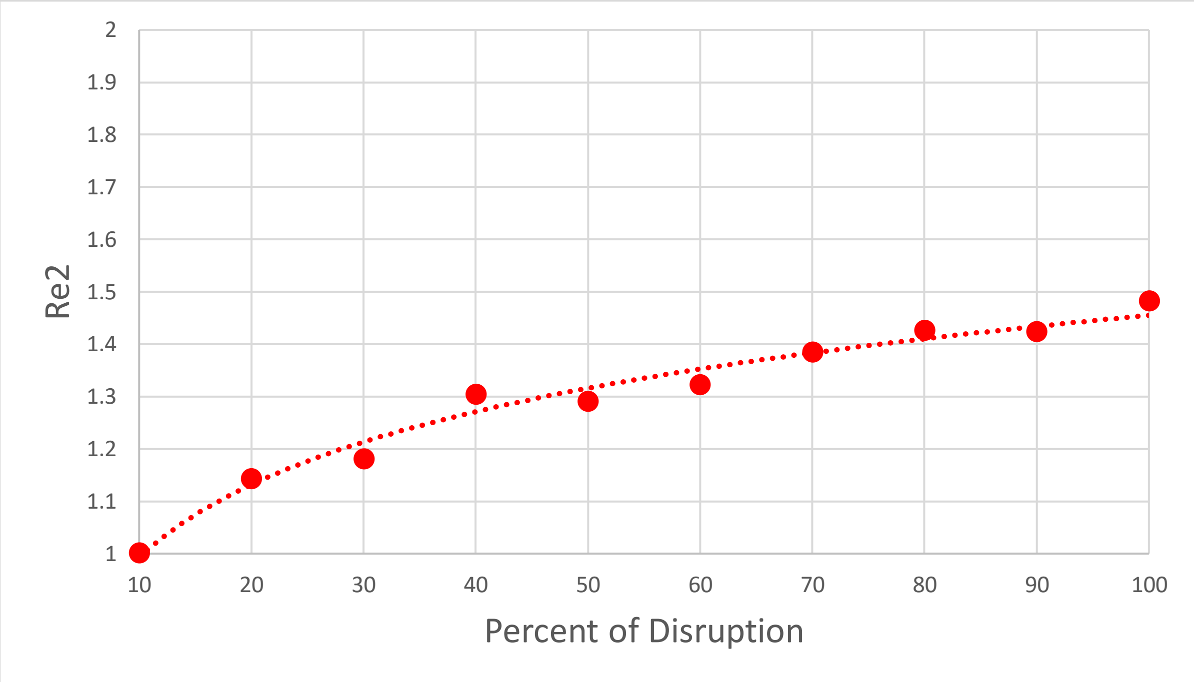


Figure 5 Environmental resiliency measure (Re2) in different scenarios

Table 4.Correlation matrix of resiliency measures

	R_T	R_S	R_{E1}	R_{E2}
R_T	1	.988**	.987**	.991**
R_S	.988**	1	.965**	.973**
R_{E1}	.987**	.965**	1	.996**
R_{E2}	.991**	.973**	.996**	1

**. Correlation is significant at the 0.01 level (2-tailed)

6. Conclusion

The study of network resiliency in speed or capacity reduction scenarios (due to natural disasters (such as floods and earthquakes) or abnormal conditions (such as vehicle accident or road maintenance sites)) 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 based on traffic-related criteria such as 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), and the two other measures are based on polluted emission 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 a new network environmental resiliency measures showed that the amount of polluted emission by vehicles under abnormal conditions increases. 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 the amount of these measures varies 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 percentages of disruption (10 to 70) are higher than high percentages of disruption (70 to 100). The results propose a nonlinear relationship between 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 makes clear the need for presenting a nonlinear relationship between percent of disruption and network resiliency measures in future studies. Besides, different traffic demand levels should be evaluated; since, 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 measures, are taken into account. On the other hand, the evaluation of these measures showed that they have a significant correlation. Therefore, in future studies, an indicator can be introduced from the combination of measures introduced in this study.

In this study, the sections in which the speed reduction occurs were selected randomly, so it is suggested that in future studies, the effect of speed reduction in pre-selected sections can be examined. 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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