Resilience Analysis of Traffic Infrastructure using Loss of Serviceability Index

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Abstract

This paper presents a methodology for assessing the resilience of traffic infrastructure in case of disruptive events, using the concept of loss of serviceability (LoS) introduced by Lentile et. al. [1]. Lentile et. al. propose a method to evaluate the resilience of traffic infrastructure using LoS index, and apply it on a case study of a motorway in Spain. In this paper, we demonstrate this methodology in a case study of the flooded area in Trier, Germany, providing insights on the vulnerability of the transportation system in the city. The insights resulting from the analysis can be used by policymakers and practitioners to improve the robustness and reliability of transportation systems in similar contexts. The LoS for all the edges in the flooded area is calculated. The produced result indicates that Kaiser-Wilhelm Brücke is the most critical edge, with respect to the flooded area and the chosen nodes around that area.

1 Introduction

With the climate changes happening rapidly and intensively, natural disasters are becoming an increasingly common occurrence all over the world [2]. Natural disasters can take different forms, such as flood, tornado, and other phenomena. They can significantly and variably impact transport systems [3], which might lead to socio-economic consequences [1]. The presence of robust transportation infrastructure is essential for the development of regional and global communities [1]. Therefore, it is important for countries and cities to improve their preparedness for traffic disruptions caused by natural disasters.

The objective of this paper is to identify a methodology to measure the traffic network resilience and to find critical nodes and edges of transportation systems. Some areas of a city can be commonly known as vulnerable parts, where severe adversities are expected in case of natural calamities, and these can cause troublesome interruptions in traffic. Therefore, a measure of network resilience is important as it provides useful insight on how to improve the road network by identifying the critical areas which need to be given more attention and investment. With the purpose of demonstration, this methodology then is applied to a case study in Trier, Germany, in the event of floods, to measure the city's network resilience and identify which parts of Trier will cause more disturbance to the traffic mobility.

In order to achieve the objective stated above, first and foremost, definitions of resilience of traffic systems must be in place. Secondly, based on the defined resilience, measures of resilience are formulated. Finally, analysis of resilience measures is conducted to provide insights of the system's robustness. The goal of the case study mentioned earlier is to demonstrate how the chosen methodology of LoS index works and its ability to produce insightful results, utilizing traffic data from OpenStreetMap and OSMnx python library. Actual flooded area in Trier and crucial nodes, i.e., hospitals, fire stations, and residential and commercial areas are selected, then LoS index is calculated in consideration of those chosen area and nodes. Based on LoS index calculation results, critical edges are identified. Critical edges are the edges which cause the most severe impacts, in case they are disrupted.

Regarding definitions of resilience, quantitative perspective is the main focus, as the objective is to measure resilience of transportation infrastructure. Quantitative measures are discussed and introduced by several scientific research, those measures include probability of susceptibility, consequence of the disruptive events in terms of economic costs and additional travel time or distance, time for the system to recover, the most severe disruption level from which the traffic infrastructure can bounce back, etc. This research bases mainly on data of traffic infrastructure, i.e., network modelled as graph structure, speed limit, travel distance, etc., therefore consequence of the disruptive events in terms of additional travel time or distance are considered suitable for a measure of resilience.

As a measure of network resilience, an index to calculate the Loss of Serviceability [1] is used. The index takes into consideration the interaction of the affected areas and the non-affected areas and is based on the change of the shortest path's travel time considering both non-degraded and degraded configuration. Critical edges in the network can be identified by using the loss of serviceability index.

2 Related Work

Vulnerability and resilience have been concerns when evaluating quality of traffic infrastructure, which have led to a considerable amount of published scientific research. In this research, vulnerability and resilience are defined in various ways, under different perspectives. The following section provides an overview of notable definitions, followed by different methods of measuring traffic infrastructure resilience.

K. Berdica defined vulnerability of a traffic system as "susceptibility to incidents that can result in considerable reductions in road network serviceability" [4]. This definition is illustrated by the graph showing relationship between vulnerability, risk, incident, and serviceability as consecutive definitions, presented in Fig. 1. According to Berdica, risk consists of two components: (1) probability i.e., the chance of an adverse event happening, and (2) consequences i.e., the severity of its resulting effects. As a sequential definition of risk, an incident is defined as an occurrence that can cause considerable decreases or interruptions in the operational capacity of a road network, either directly or indirectly. Finally, the serviceability of a road network refers to the ability to use it during a particular time frame.

Fig. 1. Relationship between relevant concepts of transportation system [4]

Based on a similar approach, Simeon C. Calvert and Maaike Snelder described vulnerability as a concept consisting of two components: probability of susceptibility and consequence for the serviceability [5]. Of those two components, only the latter is considered by Taylor and D'Este, while the first component is not taken into account or deemed unquantifiable [6]. Estimating the probabilities of uncertain events is a challenging task due to the rarity of some events, which makes it difficult to derive accurate estimates from empirical data. Agreeing with the argument of Taylor and D'Este, this paper considers vulnerability of a traffic network as "consequences for the serviceability".

Resilience of a traffic network refers to the system's ability to recover from disruptions, according to K. Berdica [4]. One can argue that resilience can be defined as the ability to achieve a new equilibrium state, however, some incidents that cause reductions in serviceability are short-lived and do not result in a new equilibrium state [4]. Goldberg decomposed resilience into two factors: (1) time to recover serviceability and (2) the most severe disruption level from which the traffic infrastructure can bounce back [7]. Bruneau et. al. described resilience as ability to decrease probabilities of incidents, ability to absorb consequences caused by occurred incidents, and ability to get back to normal states [8]. Chen and Miller-Hooks stated that a network that can recover from disruptions is referred to as resilient, the ability of the network to recover depends on its structure and the activities that can be implemented to preserve or restore service following a disaster or any other form of disruption [9]. Simeon C. Calvert & Maaike Snelder defined resilience as "the ability of a system to cope with disturbances and recover its original function after a loss of function" [5].

It should be noted that the term "to cope with" implies that resilience can be evaluated without having to measure the state of functional failure. A system that can effectively handle a disruption may be considered more resilient than one that barely manages to cope, as a more extreme disturbance could cause the latter to fail. However, even if a system experiences functional loss, it may still be regarded as resilient, though to a less severe level, if it has the ability to rapidly recover [5]. Considering opinions mentioned above, it can be noticed that, to some extent, the majority of them share similar definitions of resilience, which could be generally stated as the system's ability to maintain or recover serviceability from disruptive events. In other words, against a negative incident, the more resilient the network is, the more it can absorb from the incident and the less impacts there will be. We propose the inclusion of an additional point in this definition of resilience, based on Goldberg's second resilience factor, which is the most severe disruption level from which the traffic infrastructure can bounce back. That point is, level of resilience is determined based on the level of occurred incidents, i.e., the network's resilience varies in accordance with the severity of disruptive event.

Several methods and conceptual frameworks of evaluating resilience are proposed and presented in scientific papers. From a social and economic perspective, Taylor and M.A.P presented a framework to identify effects on accessibility of an individual to an activity rather than the accessibility between locations, which depends on three components: (1) Traveler, (2) Transport System and (3) Land use [10]. The paper provides a measurement method of accessibility based on the "inclusive value" (IV) derived from discrete choice models of multidimensional choices, which was proposed by Ben-Akiva and Lerman [11] and Train [12]. Bruneau et al. presented a conceptual framework to determine earthquake-related resilience of communities and its quantitative measures [8]. This framework is solely based on the complementary measures of resilience: "Reduced failure probabilities", "Reduced consequences from failures", and "Reduced time to recovery". The framework also introduces quantitative measures resilience's four dimensions: (1) robustness – the ability to remain functional, given a certain level of tension, (2) redundancy – level of the system's substitutability, (3) resourcefulness – the ability to recognize issues and mobilize resources when the system is being threatened, and (4) rapidity – how fast the network achieves goals. Those proposed frameworks take into account qualitative assessments and complex combination of data from different domains, other than traffic data. Therefore they are not considered in this paper, which focuses on quantitative measurements based on traffic data.

Regarding methods of measuring traffic system's resilience, Simeon C. Calvert & Maaike Snelder introduced the Link Performance Index for Resilience (LPIR), which "evaluates the resilience level of individual road sections in relation to a wider road network" [5]. By using LPIR, poorly resilient road sections and their root causes (i.e., which specific roads and traffic characteristics lead to the non-resilience) can be identified. Based on a similar approach to Goldberg[7], Simeon C. Calvert & Maaike Snelder stated that resilience consists of resistance and recovery [5]. In that paper, the definition of resistance for the traffic system refers to its ability to avoid entering a congested state when faced with a disturbance, while recovery is defined as "the ability to come out of a state of congestion". Based on definitions of resistance and recovery, LPIR is presented as a mathematical combination of those two components, which are calculated by using road characteristics (i.e., speed limit, number of lanes, road capacity, etc.), vehicle characteristics (i.e., vehicle types, vehicle dimensions, driver types, etc.), traffic information (i.e., flow, speed, and density), and temporal capacity drop caused by incidents. Focusing on the effects of reduced capacity caused by disruptive events, Lentile et. al. introduced a measure named Loss of serviceability index, based on the concept of road serviceability [1]. Adopting the definition proposed by Berdica [4], Lentile et. al. consider road serviceability as the capability of utilizing roads within a given time frame. The level of impairment to the serviceability of a road can lead to an increase in travel time, either through a decrease in the speed of a specific route or by the extension of travel distance. Loss of serviceability index takes into account additional travel time caused by disruption of the shortest path between sources and destinations. The shortest path is determined by applying Dijkstra's algorithm [13]. LoS index focuses on the consequences for the serviceability, the resilience measurement indicate level of impact of occurred incidents on the traffic network, and the method can be applied on various severity of disruptive events. Therefore, taking into account the definitions of vulnerability and resilience which we agree on, the methodology of Loss of serviceability index is deemed suitable for the purpose of this paper.

3 Research Methodology

A graph $G = (V, E)$ is a set of objects called nodes (or vertices) $V = v1, v2, ...$ and a set of edges $E = e1, e2, ...$, such that each edge ei belonging to E is associated with two nodes vp and vq belonging to V. Thus, an edge $ei = (vp, vq)$ is identified by the pair of nodes associated with it. In simplified form, a graph consist of points (nodes) connected by lines (edges). Depending on the application, the edges of a graph may have direction and it can also be that vertices or edges have an associated weight. A graph with oriented edges is called an oriented graph. When there are weights associated, the graph is called weighted [14].

Transport networks can be well represented by graphs, which allows the analysis of the structures and dynamics of infrastructures through some elements such as nodes and edges. A node is defined as a terminal point and is therefore the abstraction of a location, whereas an edge is the link between two nodes. The visualization of graphs as sets of nodes connected by links is the most practical way to represent the different network morphologies including the fundamental components of networks [15]. In the transport network, the edges represent roads and streets that are limited by nodes, the use of graph is therefore more suitable for visualization and representation, as shown in the Fig. 2 where the streets and bridges are represented by edges and the cross roads or streets ending by nodes.

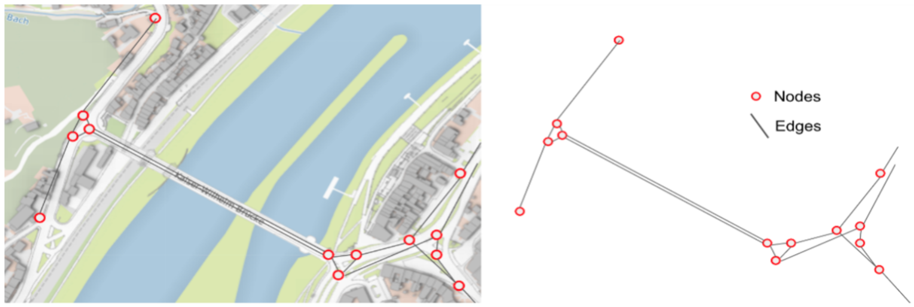

Fig. 2. Extracted road map and its graph representation of main access to Trier Kaiser Wilhelm bridge in Trier

The graph measures reflect meaningful descriptions about the node connectivity and the characteristics of edges. Some of them are used as bases for the methodology implemented in this paper, such as degree, strength, volume capacity, length and shortest path. Degree is a nodal measure that represents the total number of edges connected to a node, the strength is the sum of the weights of all edges connected to a node, and its importance is due to understand the traffic capacity of the roads. The path length is the average distance from a node to all nodes [16], defines the length of an edge as a function of its weight, the outcome is inversely proportional to the edge weight since a high weight implies a shorter connection. The Dijkstra's algorithm can be used to find the shortest path lengths between all pairs of nodes [17]. For this paper, the outcome of loss of serviceability caused by floods on some road links will be studied using different sets of patterns such as time of travel, road length, maximum travel speed.

The loss of serviceability (LoS) index is calculated after comparing the results of degraded configurations on the links of the network based on shortest path and travel time [1], the shortest path being calculated for all the selected nodes and the travel time will take into consideration the maximum speed that can be travelled. The methodology indicates the influence of the degraded road links based on indices, such that the higher the index, the more influence it has. Since the proposed methodology is made up of a network with primary and secondary roads i.e. motorways and overland routes, adjustments must be made in order to meet the necessities of a city network which includes weighting the edges in order to encompass the different traffic capacities, grouping the affected edges to get meaningful results and visualizations and choosing origin and destination points based on the necessity of the population for basic services.

The tools and resources for the chosen method are rather simple. The data required is static data and can be gathered from open sources, the manipulation of the data to reach the results can be done with open sources tools available and the computational resources for that is not demanding. As already mentioned before, the methodology proposed by [1] is suitable when applying for primary and secondary roads, since the aim is to expand the method and therefore include city network, it is believable that this method will be even more accessible.

The origins and destination nodes can be randomly defined, or in a more meaningful way the nodes can be based on the location of the essential services such as hospitals, police and fire stations and the connection to the residential and commercial areas. The use of the main streets can also be a parameter for the chosen nodes, since they tend to connect important parts of the cities. The edges, for which the LoS will be calculated, can be chosen based on main roads or even parts of the cities that can be affected by natural disasters.

The same origin and destination points have to be taken into consideration for the entire calculation of the loss of serviceability, enabling the evaluation and comparison of the different edges. For a system in which there is no occurrence of disruptive events will be called as a non-degraded configuration, meaning that the road network is fully operational. For this configuration, the Dijkstra's algorithm will be applied, then the shortest path and its travel time will be evaluated. A reference value for this scenario will then be the sum of the travel times of the shortest path.

$$\alpha_s = \sum_{i=1}^{n} \sum_{j=1}^{n} t(i,j) \tag{1}$$

- α_s is the sum of travel time of the shortest paths, given a set s of n chosen origin and destinations nodes, considering a non restricted network
- $t(i, j)$ is travel time of the shortest path from source i to destination j

A degraded configuration is when an edge of interest is eliminated. A service interruption generates a degraded configuration of the road network, and the so-called impactful edge is not available anymore from the constellation of possibilities. For this analysis, these edges shall be in the areas which are susceptible to flooding and thus increase the vulnerability of the road network. In case of flooding, new alternative paths are required to restore the link between the nodes and the travel time and/or the path lengths tend to increase and the reference value for this scenario will be the sum of the new travel times of the shortest path.

$$\beta_{k,s} = \sum_{i=1}^{n} \sum_{j=1}^{n} t(i,j) \tag{2}$$

- $\beta_{k,s}$ is the sum of travel time of the new shortest paths, given of a set s of n chosen origin and destinations nodes, assuming that edge k is disrupted
- $t(i, j)$ is travel time of the new shortest path from source i to destination j

This implies that the considered shortest paths between the origin and destination nodes change when a connected road is removed and the removed edge was also part of the path. Therefore, for each degraded edge or set of edges a new configuration for the shortest paths and their travel times is calculated, considering the same origin and destination nodes of the non-degraded configuration.

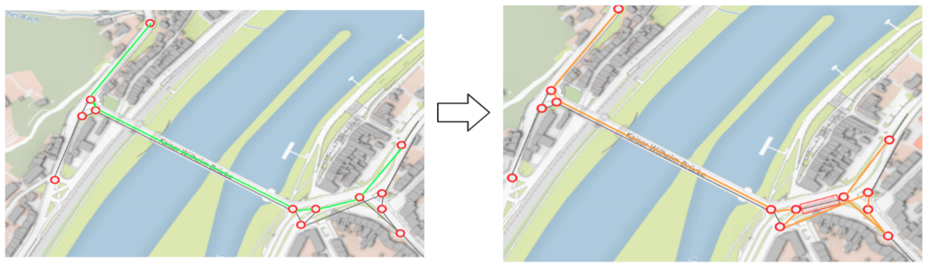

Fig. 3. Visualization Shortest path in normal conditions and the new shortest path after excluding one edge

Thus the index will take into consideration both degraded and non degraded configurations in Fig.3 and will allow the assessment of the importance of the degraded area as a link for origin and destination nodes. The higher the index, higher is the time and/or the new shortest path, the more impactful will be the missing edge for the city traffic. Therefore the indexes are going to allow the evaluation of the serviceability of the network.

The index is calculated according to the below equation whereas α_s is the sum of the shortest path and their travel time of a set s of n chosen origin and destinations nodes considering a non restricted network. For each new network layout with restricted routes where edge k of interest is removed the shortest path and their time travel are recalculated having the same origins i and destinations j nodes as reference and is represented by $\beta_{k,s}$ in the above equation. The difference is then divided by the number of paths $n_{ip,k,s}$ that crosses the removed edges.

$$LoS_{k,s} = \frac{\beta_{k,s} - \alpha_s}{n_{ip,k,s}} \tag{3}$$

The proposed index will take into account the interaction of different areas. The first is less susceptible to the loss of serviceability meaning that it works more fluidly and consistently. The second area has a higher susceptibility to disruption, so this area becomes the object of study for the identification of more crucial areas. Hence the LoS index will expose edges that are core to the network and even being crucial for the traffic flow and is still exposed to the occurrence of disruptive events. Therefore, early identification of such fundamentals edges of a network is decisive for helping the resource distribution.

4 Trier as a Case Study

4.1 Trier Road Network

To implement our methodology, the road network of the city of Trier has been chosen as the case study. Trier is a city in Rhineland-Palatinate, a state in the southwestern part of Germany. It lies on the banks of the river Moselle, and was hit by the 2021 Western Germany flood event on 12–15 July 2021 [18]. The flood claimed more than 180 lives [18] and affected more than 40,000 people in Germany alone [19]. The flood also resulted in loss of property with insurance losses adding up to more than €7 billion, out of which around €6.5 billion were on residential buildings, household goods and businesses, and around €450 million on motor vehicles [19]. The geography of Trier and its recent flood event enables it to be the ideal city to perform an analysis on its road network and see how resilient it is to floods. An analysis of the resilience of the road network of Trier enables to identify the critical edges in the network. Critical edges are the edges which cause the most severe impacts, in case they are disrupted and LoS gives us a measure to find the criticality of these edges. Identifying the critical edges and developing alternate pathways in case of their non-serviceability, can assist in reducing losses and allow faster emergency responses by hospitals, fire stations, etc to residential areas.

4.2 Implementation

The implementation of the methodology is done using Python. The map of the city of Trier is extracted from the OSMnx library. This library extracts the road network of the city as a graph, and the nodes and edges that are present in the network are derived from it. Fig. 4 displays the extracted road network displaying the nodes marked as red points and the edges marked in blue.These are input into a data frame using geopandas library. From this data set, it is observed that the road network has 6231 edges.

The co-ordinates of the flooded map of Trier city is obtained as a separate data set from [20]. The flooded area is selected in such a way that the residential areas in the cities is captured. The flooded area is constructed from these co-ordinates using shapely library. Using OSMnx the roads that are in the flooded area are derived from it. Similarly, this data is fed into a data frame using geopandas library. This data in addition to two bridges, Römerbrücke and Kaiser-Wilhelm-Brücke is taken as the flooded road network. The flooded area is known to have 173 edges within its road network.

The aim is to calculate the road network resilience of the flooded area. As a measure of resilience, the LoS is calculated for each of the 173 edges in the flooded area and they are marked according to the different values of LoS. The flooded area has been chosen in order to identify the critical edges in case a flood occurs and to have this data available for future remedial work.

To calculate LoS, fire stations and hospitals are used as source nodes. A total of 12 of these emergency stations, which are selected randomly from the map of Trier, are extracted using an OSM query. The destination nodes include 12 residential or commercial properties, most of which are chosen close to the flooded area. They are extracted using OSM as well. Fig. 5 displays the sources and destinations that are selected. The source and destination nodes are chosen such that it enables the first responders to have accessibility to the residential

Fig. 4. Extracted road network of Trier displaying the nodes in red and edges in blue

and commercial properties in case of flood emergencies. Selecting 24 source and destination nodes allows to cover a broad area of the city region.

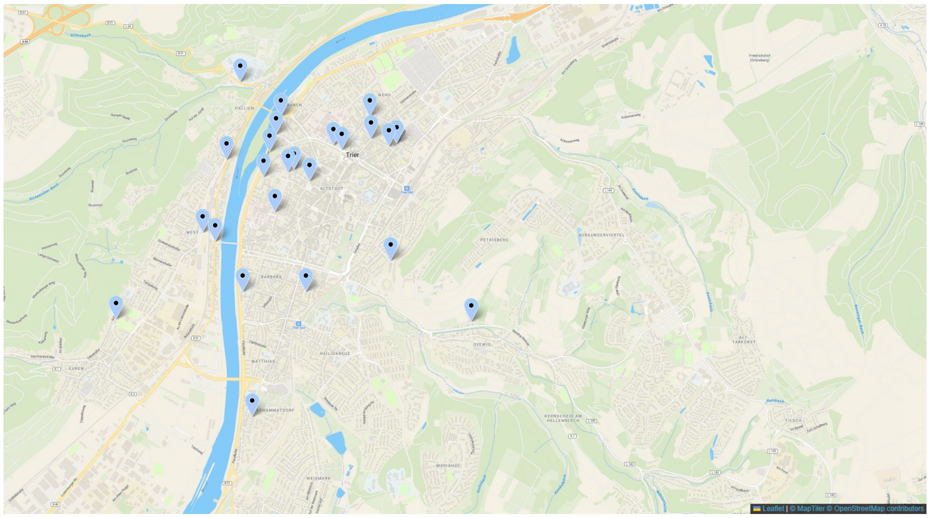

Fig. 5. The sources (fire stations and hospitals) and destinations (residential or commercial properties) that are selected

If we consider a source and a destination, the shortest path between both of them is calculated using the Dijkstra's algorithm. All the edges that are present in this path are retrieved. Out of these edges, only those edges which are present in the flooded area are selected. For each of the edges in the flooded area, the workflow in Fig. 6 is applied. The number of affected paths is the number of edges that are added in the shortest path with the removal of the edge in consideration. The added time taken is the total travel duration added with the removal of the edge. Using this workflow, the number of affected paths and added travel time, for all the edges, are calculated. These values are then stored in the data frame of the corresponding edge. Similarly, the procedure is repeated for all pairs of sources and destinations.

For all the edges in the flooded area, all the number of affected paths and added time calculated earlier are added. Hence, we get the total number of affected paths, n and the total time lost for all these edges, T. The LoS for the edges are then calculated by (4).

$$LoS = \frac{T}{n} \tag{4}$$

Based on the LoS values calculated for the edges in the flooded area, a network resilience analysis can be performed. The LoS values are calculated and displayed in terms of a table containing the edges with their LoS values. The

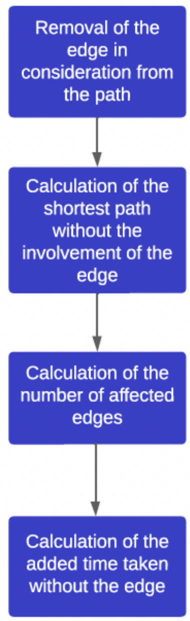

Fig. 6. Workflow: Affected paths and loss of time calculation

edges that are not visible in the table have a LoS value of 0. The results are also displayed as a bar graph with the edges in the flooded area and their respective LoS values. The edges that are not visible in the bar graph have a zero LoS value.

4.3 Results

The results of this methodology helps to have a better understanding of the road network resilience of the flooded area of Trier city. The LoS values are used as a measure of the resilience and help determine the critical edges in the network. The results show that the edges have a range of different LoS values. Higher the value, more critical is the edge. The criticality of an edge is lower if it has subsequently low LoS values. Zero value for LoS of an edge could mean that either the road is not critical or it was not used while calculating the shortest path between nodes as the nodes have been selectively chosen.

Fig. 7 shows a subset of the total edges in the flooded area. The table contains 20 edges and their information. In the table, u represents one node of the edge and v represents the other node. affected_path is the total number of edges that are affected by the removal of the edge while calculating the shortest path. time_deference is the total time duration added after the removal of the edge. Finally, the table shows the LoS value of the edges which are a measure of the resilience of the network.

	u	v	name	affected_path	time_difference	LOS
0	7741552929	9265904903	1 Römerbrücke Name: name, dtype: object	42	3339	79.5
1	9265904903	20834070	3 Römerbrücke Name: name, dtype: object	42	3339	79.5
2	3258357802	3258357818	151 Krahnenufer Name: name, dtype: object	19	103	5.421053
3	3258357818	3258357805	153 Katharinenufer Name: name, dtype: object	19	103	5.421053
4	3258357805	9051264526	152 Katharinenufer Name: name, dtype: object	19	103	5.421053
5	1651827294	344111833	62 Friedrich-Ebert-Allee Name: name, dtype:...	46	1519	33.021739
6	344111833	20833915	50 Friedrich-Ebert-Allee Name: name, dtype:...	46	1519	33.021739
7	20833915	2897253810	8 Nordallee Name: name, dtype: object	46	1519	33.021739
8	2897253810	3889178192	66 Nordallee Name: name, dtype: object	63	5446	86.444444
9	3889178192	247373153	72 Nordallee Name: name, dtype: object	63	5446	86.444444
10	247373153	20833912	45 Nordallee Name: name, dtype: object	51	3753	73.588235
11	60366894	89989804	12 Ascoli Piceno Straße Name: name, dtype: ...	9	107	11.888889
12	89989804	1622444428	13 Ascoli Piceno Straße Name: name, dtype: ...	9	107	11.888889
13	1622444428	1561307571	61 Ascoli Piceno Straße Name: name, dtype: ...	9	107	11.888889
14	1623976380	3254826012	99 Zurmaiener Straße Name: name, dtype: object	9	107	11.888889
15	3254826012	3255219365	101 Zeughausstraße Name: name, dtype: object	9	8	0.888889
16	3255219365	246827875	107 Zeughausstraße Name: name, dtype: object	9	107	11.888889
17	246827875	281525990	80 Zeughausstraße Name: name, dtype: object	9	4	0.444444
18	281525990	3702183953	92 Kloschinskystraße Name: name, dtype: object	9	4	0.444444
19	3702183953	3702183957	115 Kloschinskystraße Name: name, dtype: ob...	9	107	11.888889

Fig. 7. The edges with their LoS values in tabular form

Fig. 8 shows a bar graph of the edges in the flooded area with the highest values of LoS. Fig. 9 shows a bar graph of the edges in the flooded area with the lowest values of LoS (except 0). In both the bar graphs, only those edges are plotted which have a positive LoS value. The edges with a zero LoS value are excluded from the graph. Every displayed edge is uniquely defined by a number and a street name. There are different edges with the same street name, which implies that they are different lanes of the same street, therefore they might have different LoS values. It can be seen from the bar graph that Kaiser-Wilhelm Brücke is the most critical edge, as it has the highest LoS value.

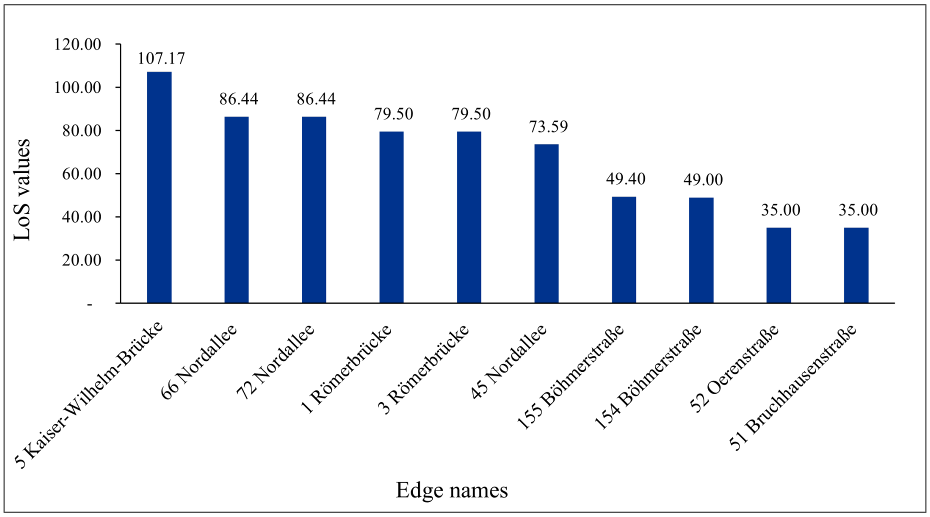

Fig. 8. The edges with the highest LoS values as a bar graph

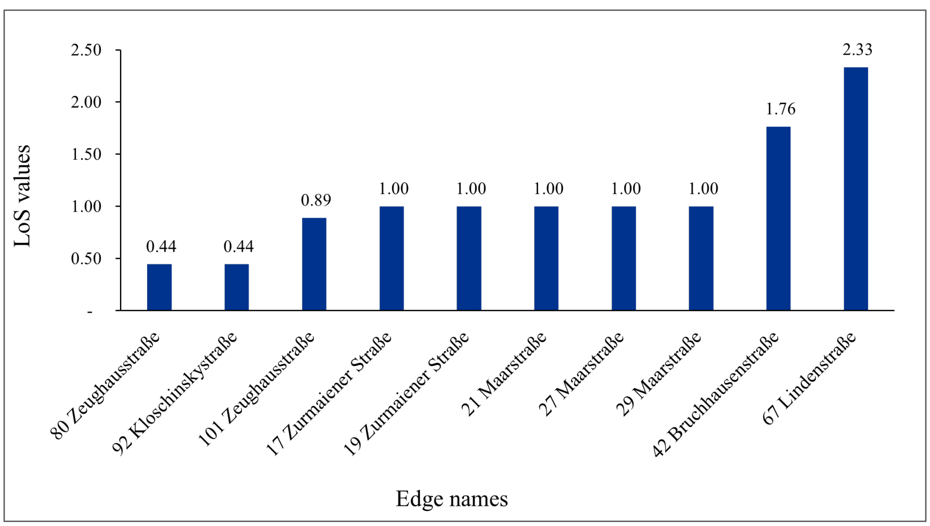

Fig. 9. The edges with the lowest LoS values as a bar graph

5 Conclusion

Resilience can be generally stated as the ability of the system to maintain or recover functionality from disruptive events. In a disrupt scenario, the more resilient the network is, the more it can absorb from the incident and the less impact the disruption is going to cause. The resiliency of the network varies according to the severity of the disruptive events and the vulnerability of individual roads/edges. Once the risk i.e. the probability and the consequences of an incident the which leads to an network failure is identified the proposed loss of serviceability index can be used to measure the edges vulnerability to obtain the measure of network resilience.

The LoS was first proposed to measure the vulnerability of edges along highway that is composed with primary(motorways) and secondary roads (overland routes). Due to the relative simple nature of the traffic data and open sources tools available this paper indented to expand the calculation of the index to identify critical edges of a city network.

Trier is cut through by the Moselle river which is a first order river and forms the shape of the city. This characteristic leads to a few particularities in the traffic firstly the bridges and the path to them are crucial points that maintain the connectivity of the network. Secondly and most important is that cities with this characteristic rely on cyclically of river flooding, which may or may not be aggravated by rainfall and other natural events. Because it is a natural and expected phenomenon, city planning cannot ignore the occurrence of these events and it is of great importance that during the occurrence of such scenarios the road network continues to connect emergency services and the population. The index proposes to identify the sections that in a flooding scenario will have the greatest impact on the connection time between nodes.

A set of 12 origin nodes and 12 destination nodes, which are residential areas, commercial areas, and emergency services, are selected. They are chosen in a way so that the nodes are around the flooded area and cross that flooded area. With respect to the flooded area and chosen nodes, LoS index is produced by applying loss of serviceability methodology. The result indicates that Kaiser-Wilhelm Brücke is the most critical edge. In other words, in case of disruption, Kaiser-Wilhelm Brücke is the nodes that causes the highest impact on the connection between chosen nodes, in terms of travel time. This result can be used by policymakers and practitioners to improve the robustness and reliability of transportation systems in Trier. This method can also be applied in other cities with similar contexts to produce insightful results.

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