Road network resilience: how to identify critical links in presence of day-to-day disruptions?

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Abstract

Several disruptive events occur on road networks on a daily basis and affect traffic flow. Resilience analysis aims at assessing the consequences of such disruptions by quantifying the ability of a network to absorb and react to adverse events. In this paper, we advance a methodological approach based on resilience stress testing and a dynamic mesoscopic simulator. By using this technique, we aim at identifying and ranking the most critical links to the overall performance of the road network, taking into account dynamic properties of road traffic. As a metric to quantify road network performance in presence of disruptions, we use the increase in overall travel cost. Then, we compare our approach with purely topological approaches.

We discuss the advantages and drawbacks of the different analyzed metrics in identifying the most critical links to the operation of the network. We prove that link ranking may vary greatly when different metrics are used. Specifically, the proposed stress testing methodology can produce very accurate results, by taking into account demand and congestion, but requires a great number of computationally intensive simulations, and is therefore prohibitive, even on medium-sized networks. Conversely, purely static topological metrics can be inaccurate if they do not take into account traffic demand and network dynamics. Our study highlights the need for joining traditional traffic-agnostic and merely topological resilience analysis with demand-aware dynamic stress-testing techniques.

1. INTRODUCTION

Road network links may be inevitably disrupted because of adverse weather conditions, human errors, or technological breakdowns. As these disruptions affect traffic flow, they may impair the ability of the transportation network to guarantee basic services, like moving people and goods, as well as emergency situation management, like providing medical and security assistance, thus causing fundamental economic and social strains.

Resilience analysis aims at predicting and evaluating the consequences of such disruptions, and has become an important research concern recently. Many authors have highlighted the need for methods to assess the consequences of transport network disruptions [1, 2]. In the field of road network, one possible approach to investigate resilience consists in identifying the links that most strongly affect the overall performance. Transportation infrastructure operators and planners should be aware of the consequences deriving from reduced capacities on links. They should focus their efforts in improving and maintaining such critical links, since they may cause the most severe consequences on traffic operations when disrupted. Thus, a methodological approach and a set of resilience metrics are fundamental to identify critical links.

Transportation networks can be conveniently represented by graphs, by modeling network intersections as nodes and links as edges [3]. This allows for exploiting graph theory and network connectivity analysis to study resilience. In the field of road network, graph theory can make resilience analysis very efficient in terms of computation costs, especially with the widespread adoption of big data technologies and cloud-computing. However, the phenomenon of congestion, which is dynamic, spatio-temporal and demand-dependent, is traditionally not addressed in many topological studies on road traffic resilience [4, 5].

In this context, our work aims at answering the following research questions:

- How is it possible to identify the links that are most critical to the operation of the whole road network?
- Which metrics are most effective in assessing the resilience of road networks, taking into account their dynamic, spatial, temporal and demand-dependent properties?
- Are topological metrics adequate to measure resilience for road networks? To which extent?

The main contributions of this paper are the following: (1) a methodology based on link-based stress testing and a dynamic mesoscopic simulator is proposed for identifying the most critical links and quantifying road network robustness; (2) the proposed methodology is compared to multiple topology-based metrics to clearly identify their limitations on a simplistic road network; (3) the approach is evaluated on a real-world road network to identify and rank the most critical links in a realistic scenario.

The paper is outlined as follows: Section 2 deals with related work on road network resilience. Then, in Section 3 we review different resilience metrics and describe our methodological approach, by presenting the stress testing approach and our dynamic mesoscopic simulator. Section 4 describes our two case studies. Section 5 reports on the evaluation of our approach in the considered case studies. A final discussion on the results is presented in Section 6, while some directions for further work are presented in Section 7.

2. LITERATURE REVIEW

In this section, we define the very general concept of resilience based on previous works, and adapt it to the context of road network analysis. Then we present road network resilience approaches to identify critical links.

2.1 Resilience definition

The most quoted definition in the literature is the one by Bruneau et al. [6], who define resilience as the ability to:

- mitigate hazards (robustness)
- contain the effects of disasters when they occur (reactivity)
- carry out recovery activities (recovery)

Sullivan et al. argue in [7] that road network robustness is the degree to which the road network can function in the presence of various capacity disruptions on component links. A robust road network can face disruptions on links with only slight increases in overall network-wide travel costs. Conversely, a non-robust road network is subject to substantial increases in network-wide travel costs.

Post-perturbation resilience of road networks is the ability to identify disruptions, mobilize resources and quickly return to an acceptable traffic flow [6]. In the rest of the paper, our definition of resilience is based on the one proposed in [7], also called robustness, as we assess the impact of disruptions on links by measuring overall travel costs.

2.2 Resilience approaches

The majority of the approaches aimed at quantifying resilience is based on topology models and network-connectivity analysis [8, 4, 5]. Similar to other complex systems, a city road system can be modeled as a graph network $G = (N, L)$ where road intersections are represented as nodes (N) and roads as links (L) [9, 10, 3].

Some research works take into account demand and measure network performance using stress testing, also called network-disruption analysis. This methodological approach has been occasionally used in the field of transportation to identify critical links in a road network [7, 11, 2]. Stress testing allows performing intra-network comparison: links are ranked based on their contribution to the overall network resilience [11, 12]. Other authors have focused on identifying only the most critical node to be improved [12]. Some studies use probability-based models to calculate the likelihood that a network continues functioning after a given stress [13, 14].

2.3 Assessment of the Literature

The definition and quantification of resilience greatly vary depending on the context and application domain. No universal and totally agreed definition or metric of resilience exists.

Despite the plethora of work on resilience in transportation and other domains (e.g., computer networks, power infrastructures, etc.), a relatively small number of studies has targeted resilience of road networks explicitly, and very few applications on real world roads have been proposed. Our paper deals instead with a real network in the Paris agglomeration area, France.

It is well-known that the concept of resilience can be divided into two parts: pre-perturbation resilience, also called robustness, and post-perturbation resilience. In this study, which is focused on traffic modeling and analysis, we evaluate pre-perturbation resilience only. By means of a simulator, we inject perturbations in the network and quantify to what degree it can adjust to them. We do not account instead for post-perturbation socio-technical actions.

As the aim of this paper is to rank and identify the most critical links in a given network, we focus on intra-network comparisons.

In the literature, two general approaches are commonly used to quantify resilience. The first is purely topological, based on graph theory and usually demand-insensitive. The second takes into account traffic network performance and includes demand variability via simulation. It is worth noting the lack of studies combining the two approaches. This study considers and compares metrics from both the approaches in order to determine their advantages and drawbacks in assessing road network resilience.

3. METHODOLOGY

We analyze and compare two different approaches to assess the resilience of road networks. Thus, we describe in the following paragraphs the topological metrics considered in our analysis as well as the stress testing technique proposed to perform demand-aware dynamic network-disruption analysis.

3.1 Graph-theory metrics

The topological metrics used in this study are based on *Betweenness-Centrality* (BC), originally proposed in [8]. It measures how central a link is in a graph by considering the number of the shortest paths that pass through the link in the network. BC represents the most widely used metric in the literature to perform traffic resilience analysis in the topological approach [15]. Additionally, BC can be computed efficiently on medium-sized networks by exploiting parallel or approximated implementations (e.g., [16]). In this paper, in order to model different aspects of a road traffic network, we also propose multiple variants of the BC, whose conventional definition on the generic link l is the following:

$$BC(l) = \sum_{i \neq l \neq j} \frac{d_{ij}(l)}{d_{ij}}, \tag{1}$$

where:

- $d_{ij}(l)$ is the number of shortest paths from node i to node j that traverse link l;
- d_{ij} is the total number of shortest paths from node i to node j.

In shortest path computation, links can be unweighted or weighted, as for example by the associated estimated travel cost (e.g., travel time). In this study, we test and compare both cases.

3.1.1 BC for entry and exit nodes only

We propose an alternative definition of BC consisting in calculating the shortest paths from entry to exit nodes only. This definition introduces two advantages: computation time is reduced; the definition seems more realistic from a demand-aware perspective, since individuals tend to start and finish their trips over a subset of intersections. This corresponds to the Origin-Destination representation of the traffic demand. The formula is the same as Eq. 1 with the following exceptions:

- i is selected from the entry-nodes subset, i.e., a limited number of intersections where vehicles enter the road network;

- j is selected from the exit-nodes subset, i.e., a limited number of intersections where vehicles leave the road network.

In conclusion, we consider four different formulations of the BC:

- Unweighted BC (BC)
- Travel-time weighted BC (TTWBC)
- Unweighted BC on entry/exit nodes only (BC entries-exits)
- Travel-time weighted BC from entry to exit nodes only (TTWBC entries-exits)

Spatio-temporal traffic properties and phenomena, like demand, congestion and dynamic re-routing, are typically not addressed in graph-based models. Thus, graph-based metrics become incapable of capturing these aspects in turn.

3.2 Demand-sensitive metric

Jenelius et al. introduced in [2] the demand-aware metric of *Importance* (I) to characterize transportation vulnerability. This metric allows measuring network performance loss by using travel costs weighted by the traffic demand. Such metric is adequate for our methodological approach as it includes demand and the dynamic phenomenon of congestion (i.e., travel costs increase when traffic is congested). This metric uses a generic notion of travel cost, that can be specified depending on the study context and aim. In this paper, we define travel cost as travel time divided by travel distance. It is therefore measured in seconds/kilometers. The Importance of a link l is defined by the following equation:

$$I(l) = \frac{\sum_i \sum_{j\neq i} x_{ij}(c^l_{ij} - c^0_{ij})}{\sum_i \sum_{j\neq i} x_{ij}}, \tag{2}$$

where:

- x_{ij} is the demand from origin node i to destination node j (measured as number of vehicles)
- c^l_{ij} is the mean travel cost from origin node i to destination node j when link l is disrupted (measured in seconds/kilometers)
- c^0_{ij} is the mean travel cost from nodes i to j in the base case (measured in seconds/kilometers)

3.3 Traffic model and algorithms

To model traffic dynamics we use a dynamic mesoscopic simulator based on the Lighthill-Whitham-Richards model [17, 18] and implemented in Matlab by our research group [19, 20].

The Lighthill-Whitham-Richards model is formulated in Lagrangian-space coordinates and uses both Lagrangian and Eulerian observations. It represents individual vehicles but only records their transit times at network nodes. A dynamic traffic assignment procedure distributes vehicles along all the possible alternative paths in the network, according to the traffic conditions at the moment the vehicle is generated. More precisely, travel times on all paths are calculated based on traffic flow, and the vehicle chooses the path that requires the smallest travel time. The following parameters have to be specified before running simulations: simulation duration, origin-destination demands and link capacities. This simulator is adequate for our stress testing approach: as opposed to static topological indicators, it includes traffic dynamic properties such as demand, congestion, traffic-based route assignment, dynamic shortest path computation and queues. Moreover, travel costs are calculated for each vehicle and can be easily extracted to compute network performance metrics, such as Importance from Eq. 2.

3.4 Stress testing

We advance a methodology based on stress testing. Its aim is to identify the most critical links in the road network and to assess its resilience, by considering the dynamic, spatio-temporal and demand-dependent properties of the network itself.

From a general point of view, stress testing consists in pushing a system beyond its normal operational capacity and observing how it responds to the applied stress. The aim is to determine its stability. Stress tests have been widely used for banking systems and in biology [21, 22].

In the field of road traffic, stress testing can be leveraged for quantifying the adverse impacts associated to a reduction of capacity on specific links. Disruptive road events such as flooding, obstacles on the road, traffic accidents are likely to reduce the capacity of a given link and negatively affect network performance. Measuring network performance loss when reducing the capacity of a given link provides the criticality of this link to the operation of the whole network.

Therefore, stress testing is an adequate methodological approach to identify and rank the most critical links in a road network. It captures the relative importance of the disrupted link to the other links and assess the overall resilience of the whole road network from an intra-network comparison.

Our methodology for road network stress testing is composed of the following steps:

1. *Simulating disruptive road events*:
   We propose two strategies to perform this step. In the first one, we simulate road disruption as link capacity drops. The *capacity-disruption level* is defined as the reduction in link capacity, expressed as a fraction of the original one. In many studies, the capacity-disruption level is total, i.e. 100% of the original value, which means that the capacity of the link is reduced to 0 vehicles per hour [10]. In other words, the link is completely removed from the road network. However, a 100% capacity-disruption level does not accurately reflect the actual link capacity resulting from frequent day-to-day disruptions or minor events (e.g. number of lane reduction, adverse weather, etc.) that can affect the network. That is why in our study we gradually reduce the capacity to analyze the evolution of the road network performance depending on the capacity-disruption level. We consider 5 capacity-disruption levels for each examined link, i.e., 0%, 20%, 40%, 60% and 80%. The capacity-disruption level of link l is formulated as follows:

   $$CDL(l) = 100 \cdot \left(1 - \frac{q^d_{max}(l, CDL)}{q^0_{max}(l)}\right), \tag{3}$$

   where:

   - $CDL(l)$ is the capacity-disruption level of link l (percentage), $CDL(l) \in \{0; 20; 40; 60; 80\}$
   - $q^d_{max}(l, CDL)$ is the capacity of link l when it is disrupted at level CDL (vehicles/hours)
   - $q^0_{max}(l)$ is the capacity of link l in the base case (vehicles/hours)

   As a second strategy to simulate disruptive road events, we consider increases in the traffic demand on specific entry/exit nodes of the network. By this approach, it is possible to simulate exceptional situations like city evacuations following extreme events (e.g., flooding, attacks, etc.) that typically put significant strain on the road infrastructure and result in total congestion of the network. This strategy consists in changing the origin-destination matrix, i.e., increasing the traffic flow from given entries, and comparing the stress testing results with another demand level.

Based on the selected strategy for disruptive road events, we set the parameters of our mesoscopic simulator (e.g., link capacity, traffic demand) and we simulate the network in the specific setting. For both strategies, travel costs are collected for all vehicles in order to compute the performance metrics described in the following point.

2. *Computing overall performance loss*:
This step is about quantifying the consequences of the simulated disruptive road event on the operation of the whole road network. To this purpose, we use the notion of road network performance, measured via the Importance metric of Eq. 2. Specifically, we consider travel time increase divided by travel distance as a measure of cost (travel time per kilometer). Below is the formulation of the overall performance loss (PL), based on the notion of importance, when a link l is disrupted:

$$PL(l, CDL) = \sum_{v=1}^{n} \frac{c_v^d(l, CDL) - c_v^0(l)}{n} \tag{4}$$

where:

- $PL(l, CDL)$ is the overall performance loss when link l is disrupted at level CDL (seconds/kilometers);
- $c_v^d(l, CDL)$ is the travel cost of vehicle v when link l is disrupted at level CDL (seconds/kilometers);
- $c_v^0(l)$ is the travel cost of vehicle v in the base case (seconds/kilometers);
- n is the number of vehicles in the network.

3. *Analyzing the results*:
At the end of our simulations, we analyze the computed results for our metrics. For each link we know the performance loss corresponding to the considered capacity-disruption level (i.e., 0%, 20%, 40%, 60% and 80% of the original link capacity). As an example, $PL(2, 40\%)$ represents the overall performance loss on link 2 when it is disrupted at 40% of its initial capacity. In the evaluation section, we will present and discuss the overall performance loss depending on the capacity-disruption level of the link in two different scenarios.

3.5 Traffic robustness index

The stress testing methodology reported in the previous section allows us to compute the overall performance loss for each link of the network with respect to five different capacity-disruption levels. In order to compare links and identify the most critical ones, we need a unique value of criticality associated to each link. To this purpose, a global metric is required to aggregate the performance loss values in the five different capacity-disruption levels. We propose the Stress Test Criticality metric (STC), defined as follows for the generic link l:

$$STC(l) = \int_{CDL(l)} PL(l, CDL), \tag{5}$$

where:

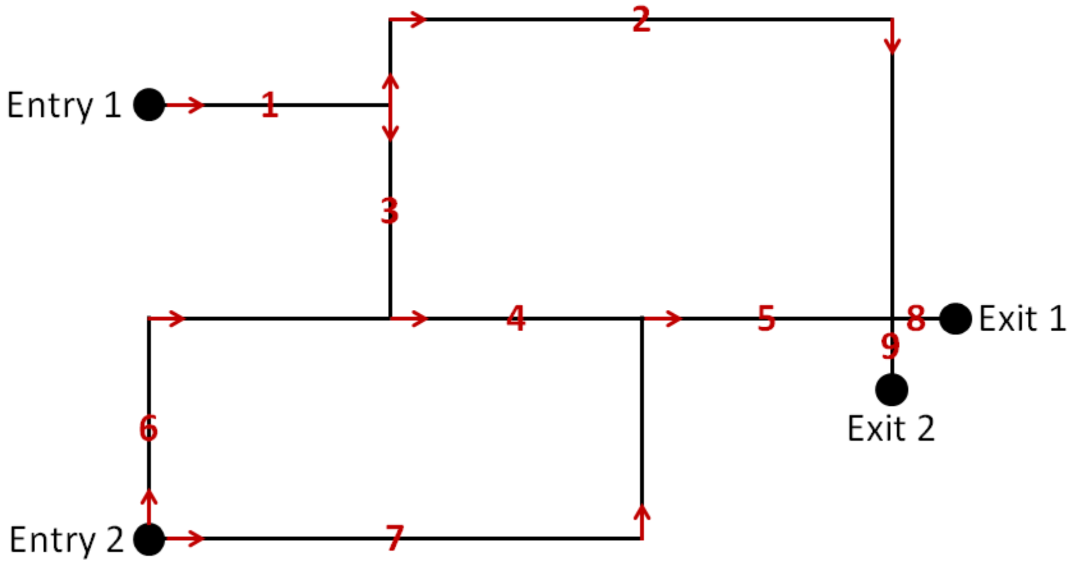


Figure 1: Simple virtual road network

- $STC(l)$ is the Stress Test Criticality when link l is stress-tested (seconds/kilometers)
- $CDL(l)$ is the capacity-disruption level of link l (percentage)
- $PL(l, CDL)$ is the overall performance loss (seconds/kilometers)

We use the trapezoid rule to approximate the integral in Eq. 5 from the (five) overall performance values computed on link l.

4. CASE STUDIES

The methodology and metrics described in the previous sections have been evaluated on two different case studies: the first one is related to a simple virtual network, used as a basic testbed for our approach; the second one is a real road network in France, which we use to confirm the validity of our results in a realistic scenario and to support the discussion on advantages and drawbacks of both simulation-based stress testing and topological metrics. The two networks are detailed in the following.

4.1 A simple virtual road network

Our simple virtual network is composed of 9 links (roads) and 8 nodes. Nodes correspond to 4 road intersections, 2 entry points and 2 exits. We remind the reader here that entry and exit points are nodes where vehicles can respectively enter and leave the network in our simulations and are used to represent traffic demand in the form of Origin-Destination matrices. The duration of each simulation is fixed to 10 minutes.

Figure 1 depicts the network with numbered links and flow directions. The network has been tested with two different demand levels, reported as two different origin-destination matrices in Table 1.

Origin \ Destination	Exit 1	Exit 2
Entry 1	375	375
Entry 2	250	1000

Origin \ Destination	Exit 1	Exit 2
Entry 1	500	500
Entry 2	1200	300

Table 1: Origin-destination matrices for the simple virtual network with different demand levels (A and B). Values are expressed as vehicles per hour.

4.2 DIRIF: a real-world road network

The DIRIF network is situated in South of Paris, France. It has 868 links and 827 nodes (657 intersections, 86 entries and 84 exits). Its roads are mostly highways. Each simulation duration is fixed to 15 minutes. As the network is much bigger than the one in Sec. 5.1, and as traffic flow can be very low on some links, we specify a higher simulation duration to ensure that enough vehicles may travel through the whole network and that we have a proper number of travel cost observations. Simulation is performed with real demand data from 9:00 AM to 9:15 AM, corresponding to the morning peak-time, since stress tests can be more relevant (i.e., higher probability of observing performance loss) if traffic flow is high. The network is graphically presented in Fig. 3.

5. EVALUATION

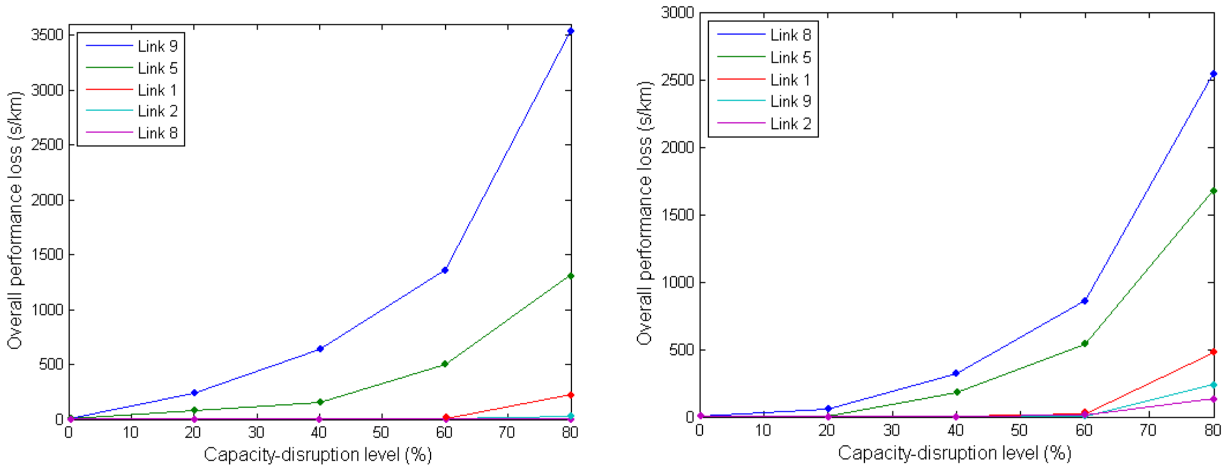
In this section, we present the results of our stress-testing methodology and discuss the link ranking derived from the different selected metrics. We show that the ranking of critical links on the same network can significantly vary when different indicators are used, thus proving that simple modifications of one centrality indicator can have a relevant impact on the capacity of the metric to capture different facets of resilience. Moreover, we discuss the advantages and drawbacks of each different approach in assessing road network resilience, and provide guidelines that can be helpful towards the definition of a new enhanced centrality metric.

5.1 Application on a simple virtual network

In the scenario of the simple network described in Section 4, we measured stress test criticality and all of the proposed topological metrics on all the links. To perform stress testing, we used both strategies described in Sec. 3.4, i.e., link capacity drop (referred as A in the following) and traffic demand increase (referred as B). The measures of stress-test criticality that result from the two strategies above are distinguished as STC A and STC B, respectively. It is worth noting that STC A and B are calculated with the same formula, but different parameters are set before stress testing.

First we discuss the results of strategy A. In our simulations, we applied sequentially five capacity-disruption levels (i.e., 0%, 20%, 40%, 60%, 80%) to each link. Then, we measured the network-wide performance loss (i.e., Eq. 4) consequent to the disruption applied to the link. The overall performance loss from our stress tests is reported as the y-axis of Figure 2, while the corresponding capacity disruption levels correspond to the x-axis. Results for different links are reported with different colors with a linear interpolation. For the sake of readability, the figure only reports the five most critical links (i.e., those with the highest overall performance loss).

Intuitively, the overall performance loss grows as the capacity-disruption level increases. In other words, a link capacity drop translates into an increase of network-wide travel cost.



(a) Scenario A (b) Scenario B

Figure 2: Stress testing on a simple test virtual network in two scenarios: performance loss for the top-5 most critical links with different capacity-disruption levels

According to the definition provided in Eq. 5, the stress test criticality of a given link corresponds to the area below its curve. Thus, in scenario A, *link 9* is the most critical to the operation of the whole road network, followed by *links 5, 1, 2* and *8*. By using link-ranking from stress test criticality as a baseline, we compare in the following the other link rankings as derived from the different selected topological metrics. Table 2 reports on such link rankings for both stress test criticality and the whole set of topological metrics.

As a preliminary consideration, it can be observed that the rankings of critical links on the same network may dramatically change depending on the selected metric, due to the different properties of the network captured by each of them. As an example, *link 5* is on top of all the topological rankings whereas, in terms of stress-test criticality, it is ranked second, below *link 9*. The top-rank of *link 5* by all the topological metrics can be motivated considering the large number of shortest paths traversing this link: e.g., paths *(4, 5)*, *(3, 4, 5)*, *(1, 3, 4, 5)*, *(6, 4, 5)*, *(7, 5, 8)* are all shortest paths.

The different ranking issued by STC A can be easily explained. If *link 5* is disrupted, the alternative paths *(1, 2, 8)* and *(1, 2, 9)* exist for all individuals departing from *entry 1*. Conversely, when *link 9* is disrupted, no alternative path exists for users willing to travel to *exit 2* from both *entry 1* and *entry 2*, thus resulting in significant congestion and consequent travel time increase for all individuals heading to *exit 2*. Additionally, traffic demand for *exit 2* is very high (see origin destination matrix in Table 1). That explains why *link 5* is more critical than link 9 in terms of topology, but less critical than link 9 when considering demand data, as made possible by our stress-testing methodology (based on dynamic simulations) and captured by the related criticality metric. This simple test clarifies how traditional demand-agnostic approaches may fail in properly ranking edge criticality.

Our simple test also shows that alternative paths may become shortest paths of the network as links are disrupted by adverse event, thus attracting traffic flow previously directed through the disrupted links. This represents another fundamental aspect that is impossible to capture with a static graph-based approach. However, it should be noted that this does not necessarily means that topological metrics are not good resilience indicators, but rather that graph modeling

Link	**STC A**	**STC B**	**BC**	**BC entries-exits**	**TTWBC**	**TTWBC entries-exits**
9	1st	4th	2nd	1st	4th	3rd
5	2nd	2nd	1st	1st	1st	1st
1	3rd	3rd	2nd	1st	4th	3rd
2	4th	5th	2nd	1st	9th	9th
8	5th	1st	2nd	1st	4th	3rd
6	5th	6th	9th	7th	7th	7th
4	5th	7th	2nd	7th	2nd	2nd
7	5th	8th	7th	1st	8th	7th
3	5th	8th	7th	7th	3rd	3rd

Table 2: Simple network link rankings generated by the different metrics of criticality

of transportation network should include a dynamic component (e.g., edge weights), and that betweenness centrality metrics should be rapidly re-computed after relevant network disruptions.

Another striking difference worth to analyze regards *link 2*: it is considered as one of the most critical ones according to the BC metric from entries to exits, whereas it is the least critical one for the TTWBC and the TTWBC from entries to exits. The peculiarity of *link 2* is its length: it is the longest one in the network, thus demanding more time to be travelled than the other links. Metrics like BC and BC from entries to exits are not weighted, i.e., all links are valued equally, and are consequently unable to grasp this important aspect. Differently, links with high travel times are not considered critical by the analyzed weighted approaches, because they are not often part of shortest paths. The same consideration applies to *link 7*, which is the second-longest link of the network.

Finally, it is worth noting that BC values are often clustered. In particular, the BC from entries to exits has many equal values and only 2 link ranks. Traditional topological metrics appear to have very limited capability to discriminate link criticality at a fine level. In this case, stress test criticality does not differentiate all links either, but this is due to capacity-disruption levels. For *links 8, 6, 4, 7* and *3* which are all ranked at the 5th place with the same value, both capacity-disruption and demand levels are not high enough to observe a significant performance loss compared to the base case. For example *link 8* capacity disruption does not affect the overall network performance (see Figure 2). The overall travel cost sticks to its base case value. That is why some links have the same criticality value. Then, stress test criticality differentiation between links depends on capacity-disruption and demand levels.

To further investigate this aspect, we use our second stress testing strategy B, i.e., we stress tested the same simple network with different traffic demand data, reported in Table 1. Results are shown in Figure 2 and Table 2. Link ranking changes significantly when different demand levels are used. As an example, *Link 8* becomes the most critical link, whereas in the previous case it involved no performance loss. This is due to the large increase in demand level associated to *exit 1*, which is directly connected to *link 8* (see Figure 1).

Takeaways: *Critical link ranking is highly variable as different approaches are used. Resilience analysis via topological metrics is limited in the sense that such metrics do not usually take into account traffic demand and network re-configurations following disruptive events. Conversely, the simulation-based stress testing approach is able to capture these aspects thus providing more realistic rankings via the proposed performance loss metric. Stress testing can also be used to compare different road networks and sub-networks, by analyzing their response to similar stresses. Travel-*

(a) DIRIF, geographic location (b) DIRIF network

Figure 3: The DIRIF road network in Paris agglomeration

time weighted BC produces better estimations of link criticality with respect to unweighted BC, which treats all links equally.

5.2 Application on a real road network

To confirm the results of our previous analysis in a realistic scenario, we considered Paris DIRIF road network, described in Section 4. Given the large size of this network and the high computation time associated to each network simulation[1], it was prohibitive to perform an exhaustive stress-test analysis as in the simple network case. Therefore, we decided to perform stress tests on a limited set of representative links: the three links with the highest demand, the three ones with the highest BC and three randomly selected edges with BC in three classes of values (i.e., high, medium and low). We discuss in the following only our simulations related to scenario A[2]. Table 3 reports the actual values of the considered metrics for the analyzed links[3].

Consistently with our previous analysis on the simple network, Table 3 shows that rankings of critical links vary significantly when different metrics are used. As an example, *links 95, 93, 94* have a very high value of STC A, whereas the topological metrics rate them much less critical than *links 802, 803, 607*. As pointed out in the previous section, the STC A ranking appears to be more realistic since it captures the higher criticality of *links 95, 93, 94* due to the associated higher demand (not reported due to space limitations).

On the small link subset considered in our analysis, taking into account travel times (TTWBC and TTWBC entries-exits) does not significantly change rankings, since link lengths (and therefore the average travel times) happen to be very similar on all considered links. Finally, it is worth

[1]Stress testing one link with 5 capacity drops takes more than 1 hour on an Intel Xeon E3 CPU equipped with 8 GB of RAM.

[2]Simulations for scenario B were in line with the results reported in the previous section and are not discussed due to space limitation.

[3]Differently from Table 2, we do not report metric rankings but actual values of the metrics for each analyzed link. This is motivated by the impossibility to get the full ranking for performance loss (i.e., STC).

	Link	STC A	BC	BC entries-exits	TTWBC	TTWBC entries-exits
Highest-demand links	**95**	117	2628	83	2628	83
	93	102	660	83	660	83
	94	101	1974	83	1974	83
Highest-BC links	**802**	42	192497	3029	192717	3039
	803	27	192521	3029	192741	3039
	607	27	192509	3029	192729	3039
	608	44.6	192449	3029	192669	3039
	397	15.8	83164	1139	83164	1139
	672	14.5	10	1	10	1

Table 3: DIRIF network link values generated by the different metrics of criticality

noting that in the DIRIF network, BC values (especially in the entries/exits variations) tend to significantly cluster themselves (i.e., many edges have very similar values of BC), thus exhibiting a lower discriminant power than in the case considered in Section 5.1.

Takeaways: *In a real-world scenario, stress testing proved to be a realistic and reliable approach to evaluate network resilience. Our evaluation confirms the importance of traffic demand and network dynamics for fine-grained ranking of the most vulnerable road-network links. Stress testing has however the important drawback of requiring very high execution times due to computationally intensive network simulations.*

6. DISCUSSION AND PERSPECTIVES

From the results presented in the previous sections, we summarize in the following a few guidelines for properly characterizing critical links by means of an intra-network approach in different application contexts.

Firstly, if resilience has to be evaluated in a relatively static context (e.g., network maintenance or planning), BC and TTWBC appear to be adequate. In particular, if data about demand and travel times are not available, we recommend BC, BC from entries and exits and BC on all paths from entries and exits. These indicators do not require special knowledge on network performance and demand data, but only the basic topology of the network in terms of links and intersections. If traffic demand is the only missing information, Stress Test Criticality, TTWBC and TTWBC from entries to exits should be instead preferred, since they also take into account travel time information.

If the goal is instead to achieve a more accurate characterization of network resilience, stress testing should be chosen, since it produces reliable results by taking into account traffic demand and congestion phenomena. The drawback is that it requires many computationally intensive simulation, thus being recommended only in application scenarios that allow for larger computation time, or that address small-sized (sub-)networks. Conversely, in application domains with very stringent requirements on response time (e.g., on-line vulnerability monitoring), topological indicators could be the only valuable option. However, it is worth to remark that efficient solutions are still required to compute these metrics on very large networks within reasonable computation time.

We advance that, in order to improve road network resilience analysis, future research work is needed that should consider joining graph-based approaches with demand-aware dynamic stress-testing techniques. In this context, we believe that a further improvement with topological metrics could be achieved by modeling the road network as a dynamic graph, whose link weights may change over time depending on actual traffic conditions and both structural and performance-related network properties (e.g., road capacity, real-time traffic information, etc.).

7. CONCLUSION

Identifying critical links to the overall performance is part of road network resilience and intra-network analysis. To this purpose, we have analyzed in this paper several topological metrics based on Betweenness-Centrality and proposed a stress testing approach exploiting a dynamic simulator. Stress testing appears to be a very promising solution for resilience analysis, allowing for measuring resilience in terms of the overall performance loss of the whole road network consequent to simulated link disruptions.

Our analysis shows that link ranking varies greatly when different metrics are used. As opposed to purely topological metrics, the proposed stress-testing approach takes into account demand levels and dynamic characteristics of road traffic. However, it requires much computation time and data than traditional graph-based metrics. The choice of a relevant metric for assessing road network resilience should depend on the context and the specific application requirements.

Merging static topological metrics and demand-based approaches could be of further research interest. It could be relevant to adopt dynamic graphs modeling, using link weights to include dynamic information on the network. In such approach, topological metrics should be dynamically computed by means of efficient quasi real-time solutions.

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