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Transportation Research Record

A Graph-based Approach with Simulated Traffic Dynamics for the Analysis of Transportation Resilience in Smart Cities

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1 A Graph-based Approach with Simulated Traffic Dynamics
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1 **Abstract**

2 Large urban areas are vital for the economic and social development of modern cities. The
3 mobility in these areas strongly depends on a seamless and available multi-modal transport
4 infrastructure network. Since many of these networks operates at capacity limits, any disruptions
5 of a single edge can have negative effects on the mobility. Hence, modeling and quantifying the
6 resilience of large-scale urban transport networks will allow cities guaranteeing higher quality of
7 service, even in the presence of unpredictable disruptive events.

8 This paper aims to develop a new methodology linking together topological data with traffic
9 dynamics for resilience analysis. To do so, we adopt a dynamic weighted graph approach where
10 weights are generated according to prevailing traffic conditions. Weight-extended centrality
11 measures are leveraged in order to capture the evolution of vulnerabilities. The paper also aims
12 at studying the impact of area-wide disruptions, such as snow storms or floods, insufficiently
13 explored in the literature. This is based on a stress testing approach. Our graph-based approach
14 is also supported by other analyses performed in the paper by leveraging more traditional traffic
15 indicators.

16 Results demonstrate the importance of both the spatial and temporal dimension in the
17 assessment of transport network criticality, thus stressing the importance of jointly considering
18 the topological properties and traffic dynamics in the study of transport resilience. Consequences
19 of area-wide disruptions are also proved to be different with respect to single-link failures,
20 therefore deserving a deeper characterization in the study of transport resilience.

21 ***Keywords:* Smart Transportation, Resilience, Stress Tests, Dynamic Graph**

1. INTRODUCTION

Infrastructural vulnerabilities and extreme events negatively affect the performance of transport networks. They have to be taken into account to improve transport resilience which is defined as “the ability of a system to operate under variable and unexpected conditions without substantially compromising its planned performances” [1]. Thanks to resilience, network performances could be quantified under normal conditions and when a disruptive event occurs.

Research in this field is fundamental from the perspectives of both transport authorities and travelers, since it can help the smooth operation of mobility services and support rescue operations as well. Nowadays, resilience is modeled and assessed either in a static way - mainly based on traffic network topological insights achieved by means of graph theory - or dynamically by means of simulations taking into account fairly realistic and time-varying traffic conditions. Structural and dynamical resilience analysis, often lead separately despite their complementary, are essential to a better understanding of network vulnerabilities. In addition, disturbances analysis has traditionally been focused on link disruptions whereas some events can impact entire areas [2].

For these reasons, the aim of this paper is to investigate novel solutions for resilience modeling and analyses, by trying to answer the following questions: how can we improve network resilience assessment by joining static, purely topological approaches to those based on traffic dynamics? How can we characterize and quantify, from the perspective of network resilience, the consequences stemming from disruptive events that affect entire areas of a city?

This work seeks therefore to advance state-of-the-art research in the field of resilience engineering by means of the following contributions: (1) we develop a methodology to integrate dynamic characteristics of the analyzed transport network into topological metrics that are traditionally static by means of an evolving, transport-appropriate, weighing. The obtained dynamically-weighted graph shall be able of grasping realistic and time-varying traffic-properties of the considered road network; (2) we assess the impact of area-wide disruptions by modeling, via stress tests and simulation tools, events that reduce network capacity on entire areas of the transport network, rather than considering single-link failures as done in most of the traditional approaches in resilience engineering [2]. Such an analysis aims to clearly highlight the importance of assessing area-wide disruptions in transport resilience studies; (3) we compare resilience metrics to a classical traffic-specific indicator, the macroscopic fundamental diagram (MFD) [3], which allows to characterize the performance of an entire area in terms of flow, speed and concentration.

The paper is organized as follow. Section 2 briefly surveys related work dealing with network resilience. Section 3 outlines the proposed methodology to construct a transport relevant weighing graph and the implementation of area-wide disturbances. Comparison between resilience metrics and traffic indicator is also presented at the end of the section. In Section 4, we present our case study and discuss the application of the proposed methodology to it. In Section 5, we discuss the main insights deriving from our case study and conclude our paper by also highlighting some research direction for future work.

2. LITERATURE REVIEW

2.1. Definition of resilience

Many definitions of resilience exist in the literature highlighting the lack of a universally accepted definition [4]. Since the introduction of this concept in the field of ecology [5], resilience has been studied in different domains. In communication networks, it is defined as “the ability of the network to provide and maintain an acceptable level of service in the face of various faults and challenges to normal operation” [6].

The most quoted definition is the one of Bruneau et al., [7] who breaks down the notion of resilience in three temporal phases: (1) *before perturbation*, corresponding to the notion of robustness,

1 (2) *during perturbation*, corresponding to the notion of reactivity, and (3) *after perturbation*, corre-
 2 sponding to the notion of recovery. Berckley et al. [8] extended the definition above by including a
 3 *feedback phase* corresponding to the notion of adaptability. In the field of transportation, Mattsson
 4 et al. [9] recently advocated the lack of adequate research on the topic, particularly with respect to
 5 the post-disaster phase. Since then, resilience has emerged as a vast domain of investigation, with a
 6 growing and active community. In this context, definitions, metrics and approaches stemming from
 7 other research fields and domains, such as telecommunications or computer systems and networks,
 8 are proving to be crucial in the transport domain as well [6, 10].

9 2.2. Approaches and metrics

10 Currently, the assessment of transport network resilience is led via two different major approaches:
 11 topological and dynamic. Combinations of both methods are rare but promising, based on the
 12 idea of joining graph theory with simulated or data-inferred traffic conditions. Shalaby et al. [11]
 13 and Gauthier et al. [12] compare public transport and road networks resilience quantified with
 14 both approaches. Preliminary results of [12] demonstrate the importance of this combination as
 15 topological approaches are traditionally unable to grasp the time-dependent aspects of resilience.

16 2.2.1. Topological Approaches

17 Topological approaches aim to quantify network resilience (especially according to the perspective
 18 of robustness) by looking at the connectivity properties of the network, by using graph theory.
 19 Transport networks are represented by an undirected or directed graph $G = (V, E)$, where edges
 20 (E) correspond to roads, and nodes (N) to intersections. Centrality measures are traditionally used
 21 to retrieve insights about in terms of network connectivity and accessibility. By studying various
 22 networks, with different topology, Derrible et al. [13] (28 different subway networks), Zhang et al.
 23 [14] (17 different networks from various fields) and Zhang et al. [15] (5 different kinds of network
 24 topologies) prove the importance of topological analysis to assess transport network resilience.

25 Although various centrality measures (closeness centrality, degree centrality, information cen-
 26 trality, etc.) exist, Betweenness Centrality (BC) [16] (Eq. 1) is among the preferred ones [15, 13,
 27 12, 17, 18] to identify vulnerable links (i.e., those with highest BC values) in transport networks.
 28 To have a global view of network performances and characterize the impact of disturbed scenarios,
 29 Global Efficiency (GE) [19] (Eq. 2) has also been frequently employed [20, 21, 22, 23]. It quan-
 30 tifies how efficiently information (or any other kind of flow) is exchanged over the network. Via
 31 this metric, the effect of a disturbance can be quantified by comparing the variation of GE under
 32 normal and disrupted conditions. The formal definitions of BC and GE follow:

$$33 \quad (1) \quad BC(e) = \sum_{j \neq i} \frac{\sigma_{ij}(e)}{\sigma_{ij}},$$

$$34 \quad (2) \quad GE(G) = \frac{1}{N(N-1)} \sum_{i \neq j} \frac{1}{l_{ij}},$$

35 where $\sigma_{ij}(e)$ is the number of shortest paths from node i to node j crossing edge e , σ_{ij} is the total
 36 number of shortest paths from node i to node j , N is the number of graph nodes and l_{ij} is the
 37 length of the shortest path(s) from node i to node j .

38 Based on shortest paths computations, the weighting of edges allows to consider road charac-
 39 teristics information like the travel time, important in path choice, ensures that traffic dynamics
 40 are taken into account in centrality measures. Shortest paths correspond to the sequence of edges
 41 with minimal weights connecting the path origin to its destination.

1 Topological approaches are simplistic in the sense that they do not incorporate dynamic infor-
 2 mation about traffic nor time-varying characteristics of the network. Some recent attempts have
 3 been made to consider link time-dependent costs in the graph representation of the road network:
 4 links are weighted by free flow time in [12, 24, 25], temporal metrics for time-varying graphs have
 5 been also developed in [26]. In line with our work, Cheng et al. [27, 28] and Yoo et al. [29] propose
 6 extended definitions of the centrality indicators, proving the importance of including commuter
 7 flows and temporal delays (e.g., travel times) in the computation of the centrality measures.

8 2.2.2. Dynamic approaches

9 In this category fall all the approaches and metrics for resilience assessment that take into account
 10 the dynamics of the transport systems (traffic conditions) based on simulation or machine learning
 11 solutions for estimating future dynamics from historical data.

12 These approaches characterize resilience by taking into account actual or simulated traffic dy-
 13 namics, using demand-sensitive indicators like links speed, queue length, road capacity or recovery
 14 time, as discussed in [30, 31].

15 Some metrics are based on comparisons of traffic conditions under normal and disturbed sce-
 16 narios. In [32], the authors propose two metrics, *importance* (I), computing the importance of a
 17 link by disrupting it, and *exposure* (E), computing the expected increase in travel cost for a random
 18 link failure somewhere. Based on the increase of travel cost when a disruption occurs, they are
 19 among the most popular metrics that belong to the category of dynamic approaches [12, 11, 2].

20 Even though traditionally more accurate than topological solutions, dynamic approaches are
 21 limited in turns [12]. They tend to use heavy simulations which demand large execution time, by
 22 providing sometimes unreliable indications about resilience due to the hardness to model unpre-
 23 dictable situations, while real-time data based solutions are expected to be much more realistic.

24 Therefore, real-time traffic data should be included and exploited in graph-based models for
 25 resilience analysis. That will demand for novel solutions based on big data processing aiming at
 26 efficiently mining the traffic data for resilience analysis. In this paper, based on previous work
 27 [24, 12], we dynamically and efficiently compute centrality measures on weighted graphs, allowing
 28 to take traffic dynamics into account. To do so, we use data issued from simple simulation to feed
 29 our dynamic graphs with links travel time, because we do not have access to real-time data.

30 2.3. Stress testing

31 To model and quantify disruptions and their impact on a complex system, stress test methodology,
 32 which is a common practice in bank and nuclear industries, can be effectively considered and
 33 leveraged in the transport field, with relevant applications for resilience assessment [21, 12, 33]. A
 34 stress test is a “*quantitative assessment designed to evaluate the ability of a network to perform*
 35 *adequately during and after the occurrence of hazard events*” [33]. This allows to quantifying adverse
 36 impacts caused by disruptive scenarios. Comparing these cases to initial one give information about
 37 how the network is resilient, by regarding changes in metrics. To quantify resilience, road networks
 38 can be stressed by inducing a reduction in capacity over single links or multiple links contained in
 39 a given area of the network. A large majority of existing works have mainly quantified network
 40 resilience by assessing the impact of targeted or random removal of single or very few edges or nodes
 41 [11, 34, 35, 36, 37]. Recently, in our previous work [12], we have studied link capacity reduction
 42 rather than abrupt and complete link removal. Such an approach allows to better quantifying minor
 43 daily disruptive events that result in a reduction of road capacity (e.g., a decrease in the number of
 44 road lanes). Nonetheless, various disruptive events, like floods, snow-storms, fires, etc. may easily
 45 affect entire areas and cannot be modeled by the previous approach. Jenelius et al. [2] extended
 46 the importance and exposure metrics to take into account area-wide disruptions. In their study,

1 they completely prohibit the access to the links contained in the disturbed area, representing by
 2 grid-cells. They conclude that “consequences are quite different from those of single link failures”.
 3 In the evaluation section, we compare the impacts of link-failures and area-wide disruptions, with
 4 weighted centrality measures, by gradually reducing the capacity.

5 **2.4. Macroscopic fundamental diagram**

6 In this paper, we propose to use traffic indicators based on the fundamental diagram (FD) to
 7 characterize resilience. A FD characterizes road by relating three traffic variables whose formula
 8 stems from mechanic of fluid:

$$9 \quad (3) \quad Q = V \cdot K_c = W \cdot (K_x - K_c)$$

10 where Q is the maximal capacity, V is the free flow speed, W the shock wave one, K_c represents
 11 the critical density and K_x the maximal one.

12 Introduced in late 2000s [3], the area-based FD, called Macroscopic Fundamental Diagram
 13 (MFD) relates the output flow and the number of vehicles in a large network, giving insights about
 14 the state of a zone over a road network. Already used in traffic control [38], could offer good
 15 opportunities in resilience analysis. Kim et al. [36] assess the resilience of a part of the transport
 16 network in the city of Seoul, South Korea, by using information issued from this traffic tool and by
 17 assessing some area properties as the outflow or the traffic density.

18 **3. METHODOLOGY**

19 **3.1. Construction of a dynamic graph**

20 By building on our previous work [12], we propose to adopt dynamic graphs modeling leveraging
 21 traffic conditions as time-varying weights associated to the links.

22 Road users tend to select their paths according to multiple variables, including travel time.
 23 However, we can reasonably state that paths are equally chosen by a user if they are perceived as
 24 “approximately” having the same total length, e.g., total travel time. The “*bounded rationality is*
 25 *neither the optimization nor the irrationality*” [39]. Bounded rationality corresponds to a choice
 26 done with flexible criterion with limited information processing resources and limited consideration
 27 of alternatives paths [40]. In order to improve the significance of the edge weights, we adopt a
 28 discretization process. This method provides the group of shortest paths, which represent the
 29 potential used roads, rather than the shortest one.

30 **3.2. Weighting of the centrality measures**

31 By leveraging the previously described dynamic, weighted, graph-based modeling of a road network,
 32 the BC of each edge, whose computation is based on the identification of the weighted shortest paths
 33 between each possible pairs of origin/destination via Dijkstra’s algorithm [41], becomes a function
 34 of the time. In other words, the time-dependency of the BC metric permits better capturing the
 35 actual functioning of the transport network by taking into account additional key and dynamic
 36 features of the roads, like for instance the actual or simulated travel times, neglected in the basic
 37 unweighted definition of the BC metric. We therefore observe and analyze the evolution of BC over
 38 time as a consequence of the changes taking place in the weighted graph, whose edge weights evolve
 39 both because of regular traffic dynamics (i.e., travel time variations due to congestion phenomena
 40 or travel demand changes) and, possibly, as a consequence of unpredictable events (i.e., accidents,
 41 or even the stress tests we induce to model area-wide disruptions).

1 3.3. Area-wide disruption analysis via stress testing

2 To analyze the impact of area-wide disruptions with respect to single-link failures, we simulate
 3 disturbance over the links contained in the area, in two different ways. While, in the former
 4 case, disruption is applied simultaneously over all links, in the latter it is allocated successively to
 5 each link. Consecutive results are averaged. The methodology is based on stress testing, allowing
 6 to observe system functioning when it operates beyond its normal characteristics. Capacity is
 7 progressively reduced from 20% to 80% of the initial one.

8 3.4. Implementation of the methodology

9 3.4.1. Elaboration of a dynamic graph

10 To weight our graph and model traffic dynamics, we leverage a microscopic traffic simulator called
 11 SymuVia¹, developed by our research group. The simulator represents individual vehicles by com-
 12 puting transit times at each second, based on LWR (Lighthill-Whitham-Richards) model [42, 43].
 13 The vehicles are distributed over the network, according to the traffic conditions at the moment
 14 the vehicle is generated. Before running a simulation, duration, origin-destination demands and
 15 limit speed per link have to be defined. The simulator allows for extracting speeds averaged by
 16 ten-minutes time stamps. Thus, by dividing link length by its simulated speed, we are able to
 17 weight edges by their travel time.

18 3.4.2. Weighting of the centrality measures

19 To discretize weights, we choose to group them according to their travel time. For the first interval,
 20 we consider the shortest link travel time t . All links whose length is in the range $[t, t + \alpha \cdot t]$ are
 21 considered equal and received the mean value as weight. The minimal value of the second interval
 22 is equal to $t + \alpha \cdot t$ and the maximal one is equal to $(t + \alpha \cdot t) + \alpha \cdot (t + \alpha \cdot t)$. Included links weight
 23 become the mean value of this second range. The process is iterated while the longest link travel
 24 time is not include in an interval. Then, we observe the effect of choosing α in the range $[0.1, 0.3]$.
 25 On the resulting graph, we apply *betweenness centrality* and *global efficiency*.

26 3.4.3. Stress testing

27 To simulate the capacity drop, we reduce progressively the speed limit according to the FD formula
 28 (Eq. 3). We use geographical zones defined by the French national institute of statistic and
 29 economic studies (INSEE) to analyze area-wide disruptions. The risk maps are in accordance
 30 with these areas and allows to allocate likely perturbations. Each area groups similar populations,
 31 implying that the size of the zone is relatively smaller especially in largely populated areas.

32 3.4.4. Traffic-specific indicator results

33 We choose to compare resilience metrics with macroscopic fundamental diagram. In our case,
 34 simulation set up are the following ones: maximal density is equal to 0.17 vehicles per meter and
 35 shock wave speed is about 5.88 meter per second. These characteristics do not change because
 36 there are defined per vehicle types (e.g. car, bus, trolley bus). The link speeds could be extracted
 37 from simulations. By summing the maximal density, k_x , of all links and their speeds, v and w , we
 38 obtain the maximal flow, q , and the critical density, k_c , with the same formula of the one used for
 39 the FD (Eq. 3). Therefore, we obtain information about a part or the entire network, according
 40 to the links taken into account.

¹<http://www.licit-lyon.eu/themes/realisations/plateformes/symuvia/>

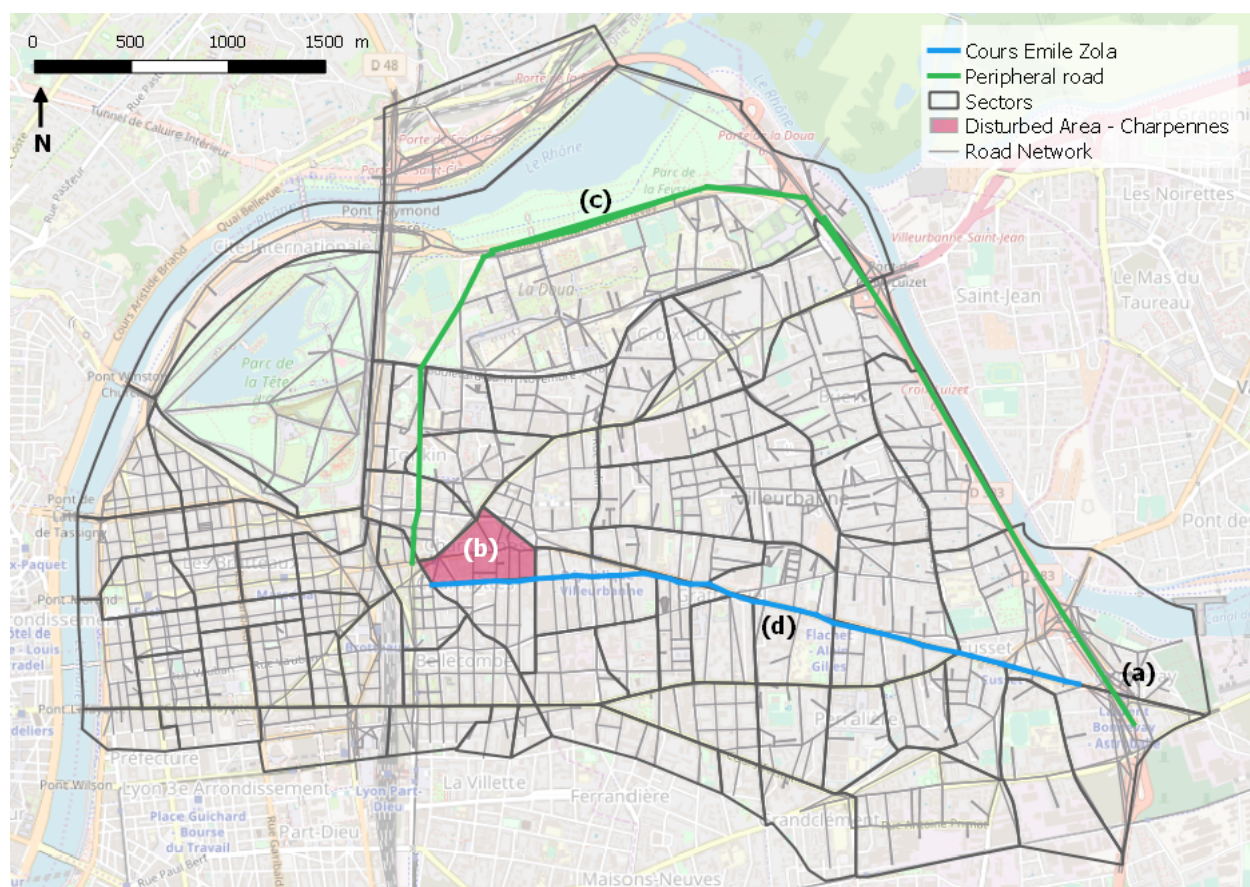


Figure 1: Case study - 3rd and 6th districts of Lyon and a part of Villeurbanne in France. (a) is the interchange, (b) the disturbed area “Charpennes” in section 4.4, (c) is the ring road and (d) the “Cours Emile Zola”.

1 4. RESULTS

2 4.1. Case study

3 Our methodology has been evaluated on a real road network including the 3rd and 6th districts of
 4 Lyon and a part of the city of Villeurbanne in France. Such area allows to run simulation with an
 5 acceptable computation time and its size allows to observe vehicles movements. Moreover needed
 6 data, as the origin-destination matrix, are provided over this area. These three places have different
 7 social and economical characteristics. The 3rd borough is the central business district of Lyon. It
 8 is also the most populated area of the city. The 6th district has instead a dominant commercial
 9 function and a large population. These two parts of Lyon are the major tertiary centers of the
 10 city. Finally, Villeurbanne is a working-class city hosting one of the largest university of the region.
 11 The studied area comprises 1,774 nodes, 3,342 links and 68 sectors, represented as a directed graph
 12 coded in Python 3.6 by using the NetworkX library [44].

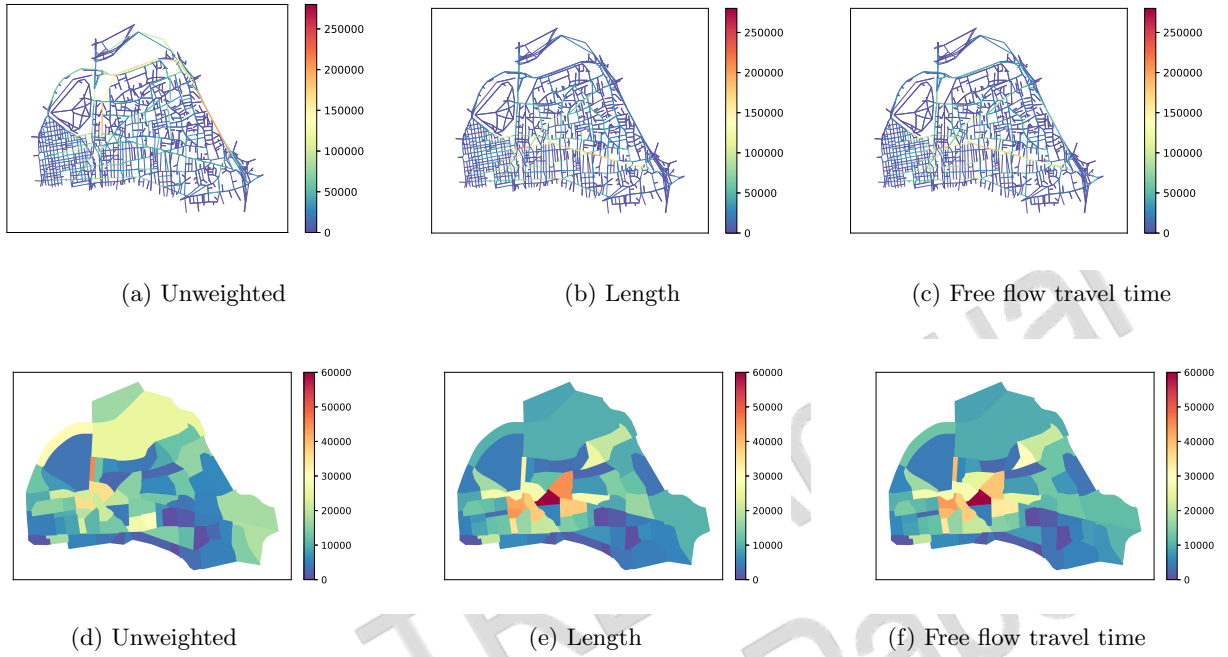


Figure 2: Comparison of unweighted, link length weighted and link travel time weighted edge BC over the studied area.

4.2. Weighting importance for BC

Weighting BC by free flow travel time is a first step towards merging static and dynamic approaches: in unweighted graphs, the length of the shortest paths is equal to the number of crossed hops. However, in realistic scenarios, the actual travel time of each road segment significantly impacts the path choice.

For the sake of simplicity, we present results per area. The zonal BC is equal to the average of the BC value associated to each link comprised within the given zone.

In Fig. 2a, we present the values of unweighted edge BC. The ring road, represented in green (Fig. 1c), possesses the highest BC due to the long length of the corresponding road segments. For instance, this is the shortest path because of the low number of crossed hops, to go from the interchange (Fig. 1a) to the red sector (Fig. 1b).

Taking length into account (Fig. 2b), the shortest path for same origin destination becomes “Cours Emile Zola” (Fig. 1d), with a distance of about 3km while the ring road one is approximately 6km. Due to the long length of the corresponding road segments, the ring road BC value approaches zero, which is not consistent with real world situation. Indeed, the ring road, even if longer in term of length, possesses a high limit speed, which has to be take into account in the shortest path research.

By weighting edges by their travel time, the ring road travel time benefit is considered. Fig. 2c shows an increase of ring road BC, due to its presence across some shortest paths.

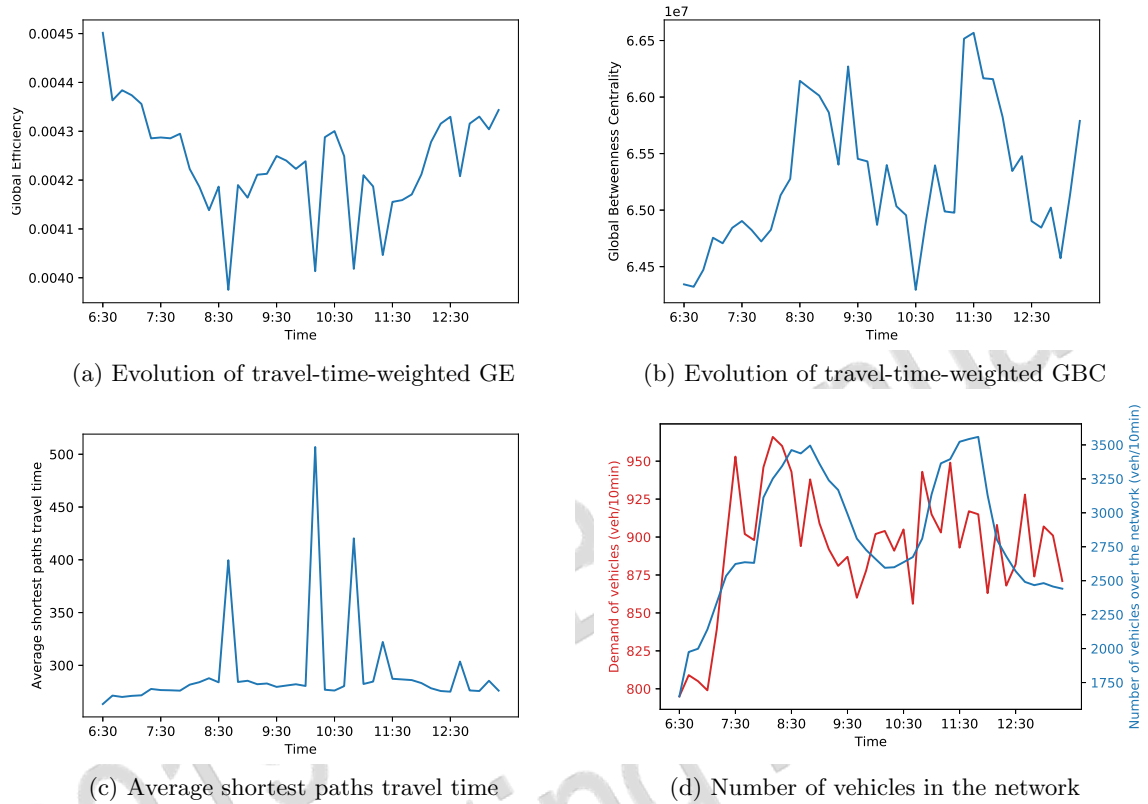


Figure 3: Evolution of the graph-based weighted metrics between 6:30am and 1:30pm.

4.3. Dynamic topological metrics

4.3.1. Evolution of network performances with “real” weights

In dynamic settings, weighted centrality measures evolve over time with traffic conditions. In our paper, the average travel times per ten minutes are derived from simulated scenario, performed from 6:30am to 1:30pm under normal conditions.

The results, graphically presented in Fig. 3, highlight a change in global performance over time, related to the evolution of vehicle number in response to the input demand, both reported in Fig. 3d. With the increase of vehicles present over the network, the GE (Fig. 3a) drops whereas the sum of the BC computed over all links, named in the following *global betweenness centrality* (GBC) rises. The change in performance means that the network is unbalanced, i.e. there are certain links traversed by more shortest paths (and therefore typically attracting more traffic) than other ones.

The appearance of traffic slowdowns increases the travel time of the traversed links. Thus, the value of travel time associated to the shortest paths at the successive time slots rises. The two following situations can occur: either vehicles continue traversing the same path, which will show, in the following time slots, a larger travel time because of congestion, or vehicles switch to a new path, which has a certain travel time, very likely larger than the one traversed during the previous time slot. The global increase of travel time associated to the different paths leads therefore to a decrease of GE (Fig. 3a), inversely proportional to the length (i.e., total travel time) of the shortest paths (Fig. 3c). This aspect is underscored at 8:40am, 10:10am and 11:20am. Interestingly, an opposite trend can be observed in relation to GBC: the spikes for GBC (Fig. 3b) can be explained

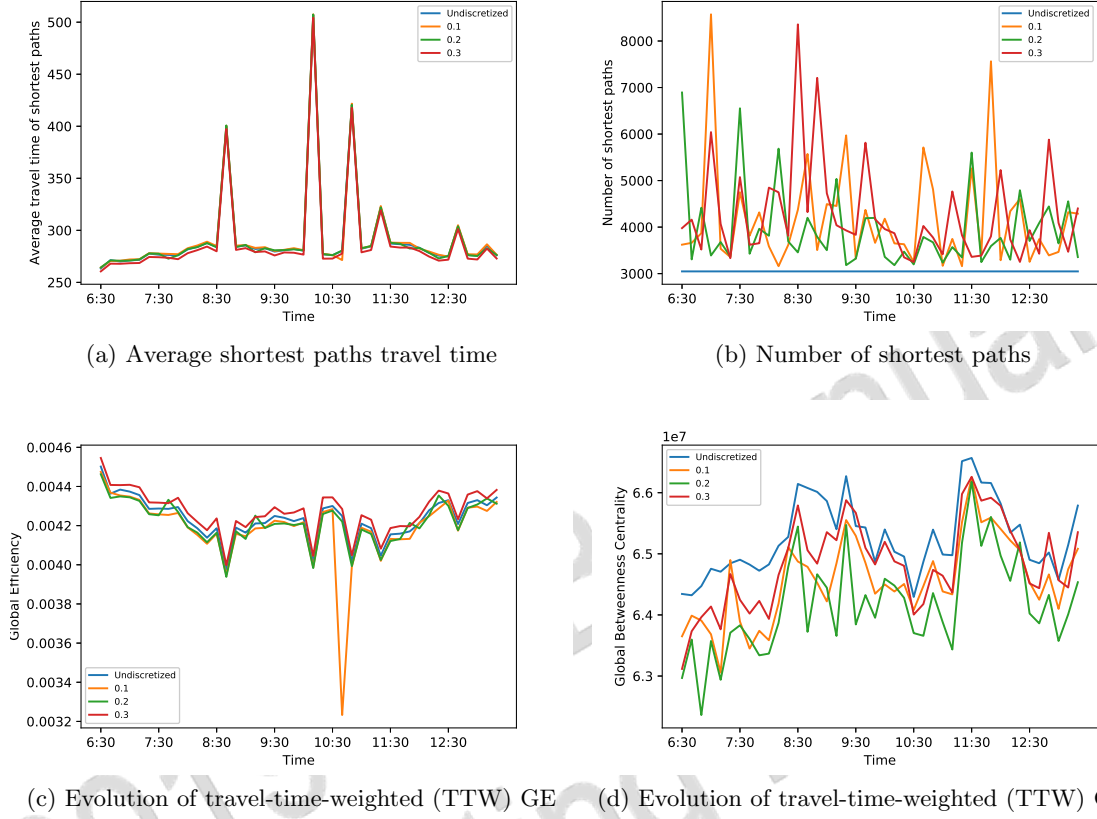


Figure 4: Evolution of the graph-based weighted metrics between 6:30am and 1:30pm for discretized weights $[t, \alpha \cdot t]$ and different values of α under normal conditions.

- 1 by considering the relatively higher number of links traversed by a large number of shortest paths,
- 2 meaning that the network becomes strongly unbalanced at demand peaks. In other words, more
- 3 and more links become critical, raising the global GBC indicator.

4 4.3.2. Evolution of network performances with discretized weights

5 According to the users bounded rationality principle, the path choice has to be less demanding to
 6 obtain a resilience analysis relating to network usage rather than the use of the shortest path only.
 7 For that, we discretize edges weights in order to obtain a group of paths approximately equal (from
 8 the user's perspective) to the shortest one and take them into account while computing centrality
 9 measures. The applied discretization, detailed in Section 3.4., consists in grouping similar weights
 10 with intervals defined as follow: $[t, t + \alpha \cdot t]$. The weight discretization is analyzed for α varying
 11 from 0.1 to 0.3. Higher values are not realistic because they assume that a path whose travel time
 12 increased by almost half of the shortest one is perceived as equivalent by the driver. With the
 13 increase of shortest paths number (Fig. 4b), observed for α equal to 0.1 to 0.3, more possibilities
 14 exist to join two nodes regarding the BC definition. In traffic perspective, this implies that BC will
 15 capture the criticality of the possible taken paths by drivers rather than the topologically shortest
 16 one. We chose to allocate the mean values of corresponding interval to edges but it could also be
 17 done with the maximal one, which would only impact GE. The global metric would be lower with
 18 the same trend, because of the increase of travel time. Used paths are distributed over different
 19 roads for the same origin destination, reproducing the actual users behaviors.

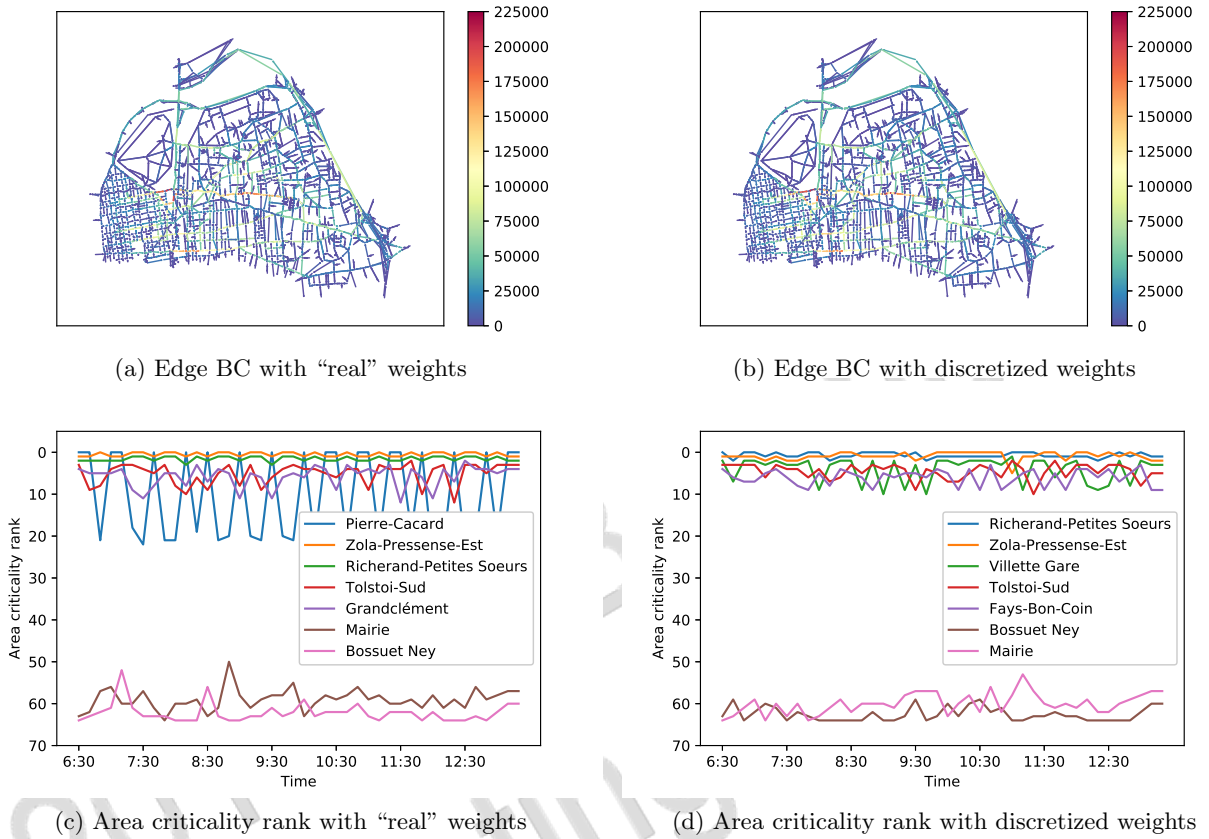


Figure 5: Link distribution of BC over the network at 8:30am and rank of five originally most critical areas and two less ones according to their BC under normal conditions.

1 About centrality measures, at the global level, only slightly changes are visible, in case of
 2 discretized weights. Indeed, Fig. 4d and 4c present almost superimposed curves like the average
 3 paths travel time for all origins destinations (Fig. 4a). Nevertheless, we can observe that a small
 4 change in average shortest path travel time could have huge impact on GE (a peak is present at
 5 10:40am for an α value equal to 0.1 and at the same time the average shortest path travel time
 6 is a bit reduced). The evolution of the weighted topological global metrics mostly depends of the
 7 vehicles number and not to their road usage.

8 At local scale (Fig. 5), the change in edges BC distribution at 8:30am is not really impacted
 9 (Fig. 5a and Fig. 5b). By ranking the five most critical areas and the two less critical ones in both
 10 weighting cases (Fig. 5c and Fig. 5d), we capture the discretization effect due to the new shortest
 11 path distribution. Some areas are thus crossed by these new paths, captured in the centrality
 12 measures, using the discretization. Nonetheless, in free flow conditions, the discretization does not
 13 have a big influence over the results.

14 4.3.3. Evolution of network performances with discretized weights in congested situation

15 To observe the impact of discretization in presence of congestion, we run a simulation from 6:30am
 16 to 1:30pm in presence of a blockage. At global level, we notice a continuously increase in the
 17 number of vehicles over the network (Fig. 6c. This implies a global decrease of performances (Fig.

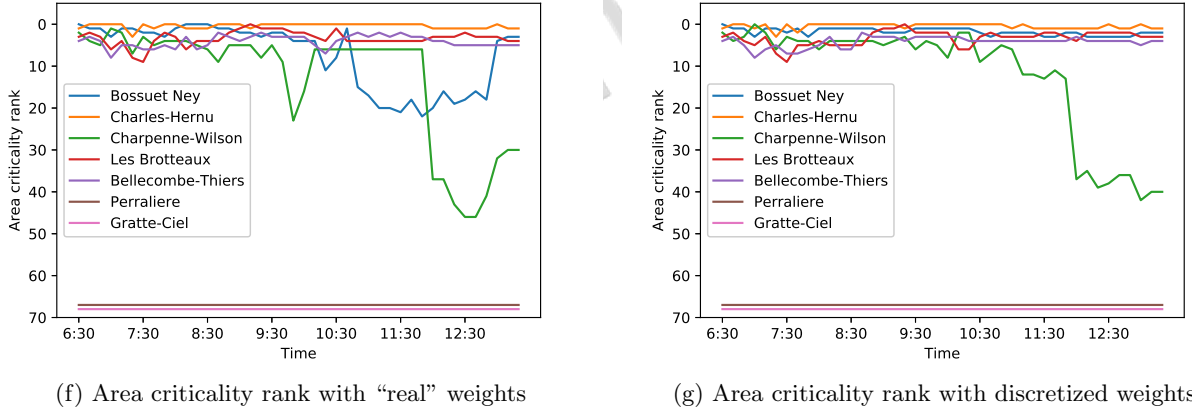
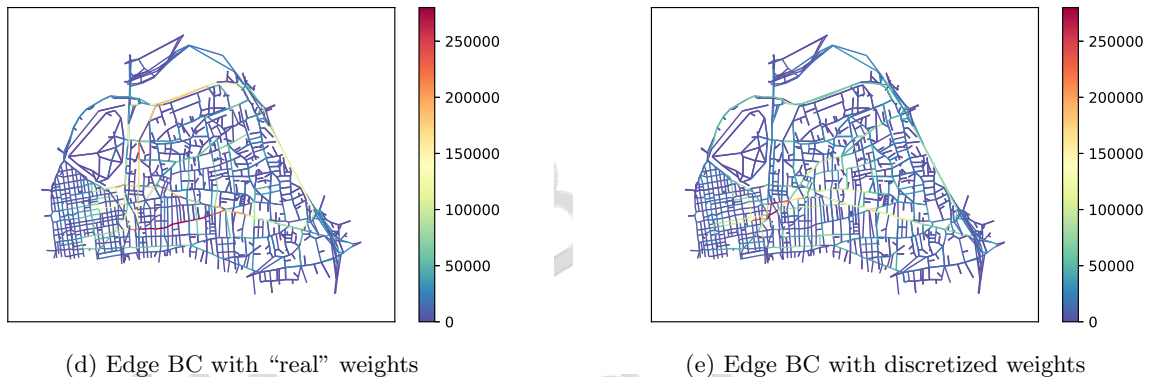
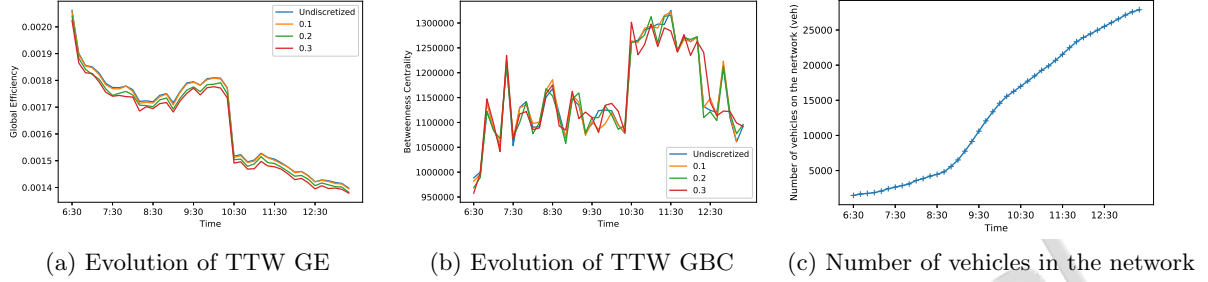


Figure 6: Evolution of the graph-based weighted metrics between 6:30am and 1:30pm for discretized weights $[t, \alpha \cdot t]$ and different values of α in presence of congestion at global and edges BC distributions at 8:30am and area ranking at local levels.

1 6a and Fig. 6b) with the reduction of GE and the increased peaks of BC. Global results still does
 2 not change significantly with the discretization.
 3 Nevertheless, at local scale, the distribution of edge BC is completely different at 8:30am. The
 4 various distributions of criticality are related to the different paths used without and with discretized
 5 weights. In the non-discretized weights case (Fig. 6d) some roads are distinguished by their BC
 6 value as the ring road. When weights are discretized (Fig. 6e) BC is slightly better distributed over
 7 the network, although we see a group of critical links close to the center of the network. The ranking
 8 of the five originally most critical areas and the two less ones over time, are realized with (Fig. 6g)

1 and without (Fig. 6f) discretized weights. With the second weighting option, positions of areas in
 2 ranking are more stable. This is the result of the better distribution in road usages. The increase
 3 of travel over a link is mostly absorbed by its equivalent paths. It does not always imply a change
 4 in path, like for the non-discretized scenario. In both cases, the rank of “Charpennes”, represented
 5 in green, declines. At 10:30am, contained links begin to clog up. The shortest paths change and
 6 pass through new areas. Its BC decreases, causing an important rank fall from 10:30am to the end
 7 of the simulation. As it corresponds to the appearance of a strong and sustained congestion, this
 8 area requires a particular attention. On the contrary, lowest-ranked areas, which conserve their
 9 positions in the rank from 6:30am to 1:30pm. Because they are constitute of links with long travel
 10 time or because they are outermost than other areas, they are less crossed and thus less critical.

11 4.4. Impact of the discretization of weights

12 At global scale (GBC and GE), the discretization of weights does not impact results a lot. The
 13 evolution of both metrics follow the same trend in both weighting methods. As the BC is dependent
 14 on the shortest paths number and composition, by increasing them via our discretization method,
 15 redundant shortest paths exist for a same itinerary and therefore more links are crossed. The
 16 criticality is thus spread over travel-time-equivalent redundant paths, modifying results. The major
 17 impact of this step is underlined by results issued from congested simulation where edges and areas
 18 BC distributions are completely modified (Fig. 6). From the rank analysis (Fig. 5d and Fig. 6g)
 19 we can extract some lines to manage transport network. An area with a rank almost constant
 20 proves that they are “insensitive” to traffic conditions and thus have not to be monitored as a
 21 priority, whereas a fall in ranking for a part of the network is due to its congestion, therefore it
 22 is a critical part. It is related to an increase of another part which becomes crossed by shortest
 23 paths. By reproducing the use of road network by adapting edge weights, we are able to quantify
 24 network resilience in relation to both its topology and its traffic conditions. It is essential to reliably
 25 reproduce network usages for an accurate resilience analysis regarding the significant change in BC
 26 distribution.

27 4.5. Comparison between area disruptions and link failure

28 In this part, we compare the consequences of area-wide disruption with the average impact caused
 29 by the successive links disturbances. We use a graph with free flow travel time discretized weights
 30 with an α value of 0.2. Our stress tests here consist in a reduction of capacity from 20% to 80%
 31 of initial conditions. In the first case, (Fig. 7a and Fig. 7c), all links contained in the central area
 32 (Fig.1) are disturbed simultaneously by a speed reduction and thus a diminished capacity. In the
 33 second case (Fig. 7b and Fig. 7d), same links are disturbed successively. The results are averaged.

34 Regarding GE (Fig. 7f), the decreasing shape of network performances with respect of the
 35 capacity reduction is similar for both scenarios. When the capacity is disrupted and thus the
 36 speed is reduced, shortest paths travel time becomes longer by using bypass roads. By averaging
 37 the impacts of disturbance over successive links, global network performances are lower reduced
 38 than the area-wide disruption case. In the first case, the bypass consists in avoiding a unique link
 39 whereas in the second case, it has to circumvent an entire area. The new used path is longer in
 40 case of area-wide disruption, hence the greater loss of performances in term of GE.

41 To analyze the impact with BC, we focus on a capacity reduction of 60%. The results, by area,
 42 show different impacts (Fig. 7e) according to area-wide disruption (Fig. 7c) and successive link
 43 ones (Fig. 7d). Nearby sectors are greatly impacted by the used simulation of disruption contrary
 44 to the surrounding ones. Indeed, these zones are too far to be crossed by the new shortest paths.
 45 Conversely to southern areas, BC is higher in case of area-wide disruption than for link failures
 46 in the north. This is due to the existence of a bypass road for the impacted portion of “Cours

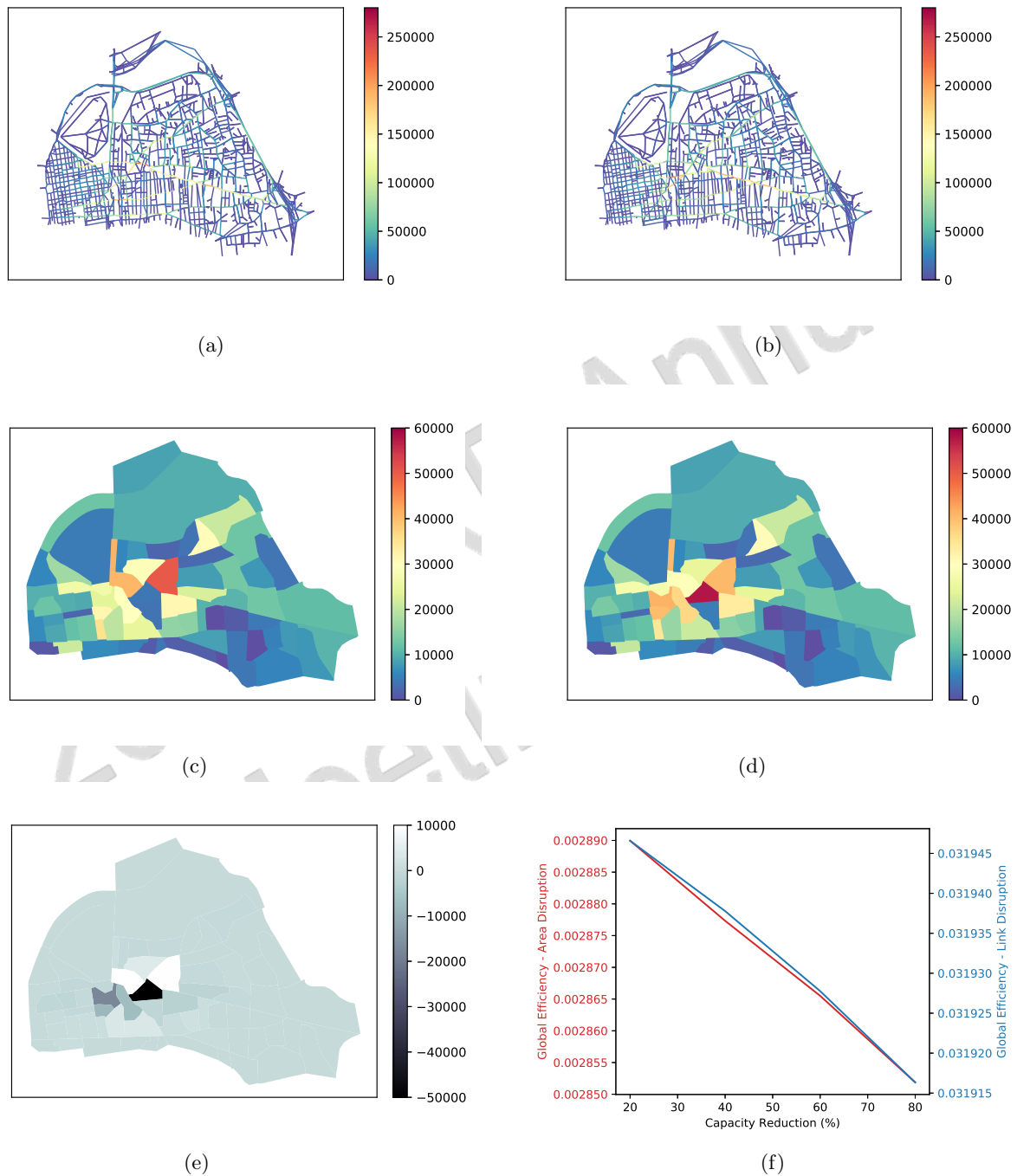


Figure 7: Results for simulation of disruption over an area by diminishing all capacity link (a) (c) or averaged results of one link capacity reduction for all contained in the area (b) (d). Differences are presented in (e) by subtracting the mean successive link disruption impacts of area-wide disruption one. Impact of these different disruptions is computed by GE on (f). In both cases, capacity during the perturbation is equal to 40% of the one under normal conditions.

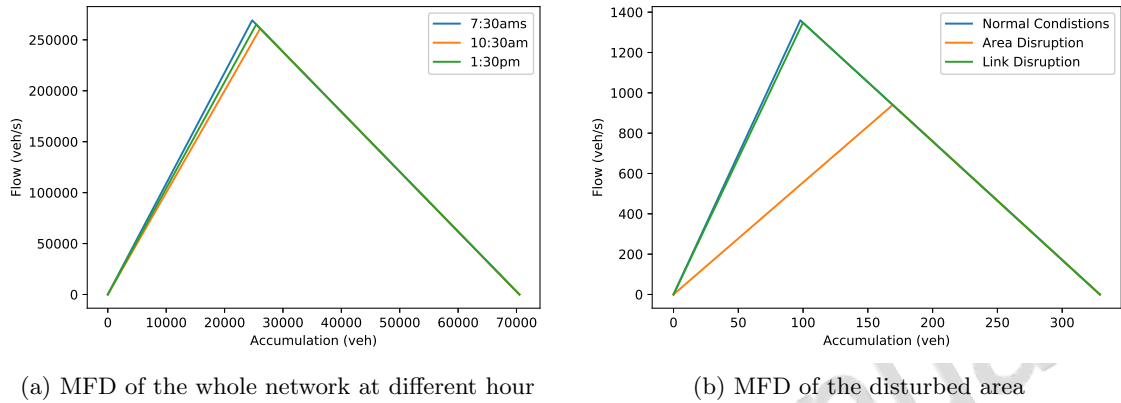


Figure 8: Macroscopic Fundamental Diagrams (MFD)

1 Emile Zola” when the whole sector is disturbed (Fig. 7a). In that situation, there is no shortest
 2 path passing through this sector, reducing its BC to almost zero. All links capacity is reduced
 3 simultaneously, deleting possible redundant paths inside the disturbed area. With successive link
 4 failures, some edges located in the disturbed area, still present a travel time benefit and therefore
 5 crossed by shortest paths (Fig. 7b). These results prove the importance to focus also on area-wide
 6 disruption in resilience analysis.

7 4.6. Traffic indicators

8 4.6.1. Evolution in time

9 To observe the evolution of global networks characteristics at different time, we plot the MFD of
 10 the whole studied network in congested situation (Fig. 8a).

11 The network capacity is the highest at 7:30am. At this time, only few vehicles are presented over
 12 the network (Fig. 3d) which operates under normal and optimal conditions. The major decrease of
 13 global capacity is observed at 10:30am. The drop of capacity is about 4000veh/s . This is related
 14 to the increase of the GBC (Fig.3b) and the decrease of GE (Fig.3a). By increasing the number
 15 of vehicles over the network, several roads become congested, reducing their speed. The maximal
 16 capacity is reduced, impacted the MFD shape and used paths are distributed over longer ones,
 17 transiting over more links.

18 Finally, at the end of the simulation time, at 1:30pm, maximal capacity is slightly improved.
 19 Network regains a part of these initial conditions. This is also the case for centrality measures.

20 4.6.2. Comparison of disruption methods

21 To compare results of disruptions methods we plot the MFD of the disturbed area (Fig. 1b).
 22 The results (Fig. 8b) are obtained under normal conditions (blue curve), with the average im-
 23 pact of successive reduction of link capacity (orange curve) and when their capacity are reduced
 24 simultaneously (green curve). The disruption consists in a reduction of 60% of the initial capacity.

25 Area-wide disruption impact is more important than for the average of the successive links
 26 failures impacts. The maximal capacity is reduced about 400veh/s . Although the consequences
 27 were greater with the resilience metrics, the trend is identical. The successive link failure method
 28 gives a MFD close to the one obtained under normal conditions (Fig. 8b). This was already the
 29 case for BC (Fig. 2f and Fig.7d).

1 4.6.3. Assessment

2 The centrality measures and the MFD are related. Indeed, a reduction of capacity implies a rise of
3 travel time causing a change to longer shortest paths with a longer sequence of crossed links.

4 5. CONCLUSION AND PERSPECTIVES

5 In this work we propose contributions to network resilience modeling and analysis by improving
6 classical topological metrics through the integration of traffic dynamics via a simulation-based
7 approach. In addition, comparisons between those metrics and the MFD are performed.

8 By means of a dynamic weighted graph, we relate static and dynamic approaches. Outcomes
9 present the heavy dependence of weights in topological metrics results. The choice of travel time
10 weighting is motivated by the analysis lead in Section 4.2. By grouping similar travel time edges,
11 reproducing accurately the users path choice, we obtain a new distribution of topological criticality,
12 consistent with traffic conditions.

13 Regarding simulation of disruptions, area-wide ones have to be chosen to reproduce effect of
14 some events like floods, social movement or power outage which impact several links over sectors.
15 Reproduction of these impacts are not possible by link failures as shown in Fig. 7. This type of
16 disruptions allows to study resilience of specific events. It could also be used to rank areas regarding
17 their criticality.

18 Finally, relations between the traffic indicator and the metrics of resilience is demonstrated. An
19 increase of BC is related to a decrease of the maximum flow in the MFD this is the ultimate goal
20 as we expect that our newly developed resilience metrics to incorporate, in an accurate manner,
21 traffic dynamics.

22 For future works, objective will be to characterize resilience of multimodal network. Thus,
23 socio-economic information for studied area will highlight about favored transport mode and num-
24 ber of trip going from or arriving in a given area.

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33 AUTHOR CONTRIBUTION STATEMENT

34 The authors confirm contribution to the paper as follows: study, conception and design: EH,
35 AF, NEEF; analysis and interpretation of results: EH, AF, NEEF; EH was the lead writer of the
36 manuscript. All authors reviewed the results and approved the final version of the manuscript.

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