DATA-DRIVEN CRITICALITY MAPS OF URBAN STREET NETWORKS

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ABSTRACT:
Urban street networks are increasingly susceptible to unplanned emergencies and disruptions triggered by natural and man-mad events. To address this issue leading to economic losses and increased social costs, efforts are currently focused on taking the necessary actions to prevent and limit the consequences from the occurrence of these adverse events.
To enhance the urban street network resilience it is pivotal to pinpoint the most critical elements taking into consideration the street network structure and the travel patterns acting on it.
In literature the former point has been widely studied: the criticality of a road network element is measured through its network centrality (betweenness, information etc.), neglecting users behavior. The possibility of tracking a huge number of private cars (Floating Car Data (FCD)) allows us to consider not only the structure of the network but also the experimental vehicles distribution. In order to take into consideration these two features (i.e. network structure and time-optimized diffusion process) we weight the calculation of centrality measures by the experimental vehicles distribution, extracted from FCD by means of zone aggregated OD (Origin-Destination) matrices.

KEYWORDS:
Road network, Criticality, Urban Mobility, Floating Car Data, Maps

1. INTRODUCTION

Growing population and increasing complexity of critical infrastructures, such as electric powers, water utilities, ICT systems and transportation networks, make urban areas more and more vulnerable to emergency situations caused by natural phenomena or acts of man.
Failure or even just temporary disruption of critical infrastructures could result in long-lasting supply bottlenecks, significant disturbances in public security or have greatly disproportionate effects that spread far beyond the immediate area of disturbance.
As a result there is a significant need to a better understanding of the contributing factors to the vulnerability of critical infrastructures so that lives can be saved and community costs can be reduced (Murray, 2007).
As regards the road network systems the concept of vulnerability is important when examining its ability to provide continuity in operation once a critical event has caused a disruptive effect on traffic flow (Mattssonn, 2015). Even if the discussion about the meaning of the term vulnerability (Mattssonn, 2015) (Murray, 2007) is still open to debate we can accept the definition of Berdica (Berdica, 2002) who intends "Vulnerability in the road transportation system" as the "susceptibility to incidents that can result in considerable reductions in road network serviceability".
It is clear that each element of the network contribute differently to the vulnerability of the network: the probability to observe an incident, the reduction to the level of service and its consequences depend on the

network elements. We can therefore define the degree of criticality of a network element as its contribution to the vulnerability of the network, i.e. the disruption of a critical element produce a considerable "reductions in road network serviceability".
Therefore a vulnerability analysis of urban road network should identifying the degree of criticality of a network element by measuring the reduction in the level of serviceability caused by its (partial or total) interruption.

According to network theory (Newmann, 2010) centrality measures represents an elegant way to identify critical elements of a network. They've been widely used to study road network structure and hierarchy mostly in urban environments (Porta, 2006), (Strano, 2013), (Jiang, 2004), (Demsar, 2008). These researches are based on an highly abstract representation of road network (usually an undirected and unweighted graph). The centrality of each network element (a node or a edge) is calculated with respect to its relevance with respect to the shortest paths (SP) ensemble (the set of shortest paths between each node couple) on the graph. Nevertheless centrality measures depends only on network topology neglecting users behavior and are grounded on a simplified network representation therefore, without any modification, they're not very suitable to identify critical links, according to the definition above.
A different approach for identifying critical links is to iteratively remove some link from the network and to estimate the consequences of its closure in terms of the reduced network ability to efficiently satisfy traffic demand. This approach is based on the application of a traffic simulation tool capable to reproduce traffic operation conditions in terms of traffic volumes and speeds on each link and to quantify the impacts at network level (Murray, 2007), (Nicholson, 1997), (Mattsson, 2015). However traffic simulation process presents high computational cost so that it is very difficult to get an insight on the criticality of each network element (Mattsson, 2015).
The problem is therefore to design a method able to assess criticality of urban road network by considering a detailed network topology and taking into account the actual traffic distribution.

Following Jelenius et al. (Jelenius, 2006) we propose to modify shortest paths-based centrality measures in order to consider traffic demand: the key idea is to weight each SP connecting node u to node v in the calculation of centrality index with a coefficient that represents the probability that a path joining u to v has been observed. As noticed by Balijepalli and Oppong (Balijepalli, 2015) shortest paths don't represent a realistic routing algorithm in urban environment as the density of the network allows drivers to find many routing alternatives. This implies that SP-based centrality measures are not able to capture criticality of road network elements in urban areas.
Nevertheless using SPs as routing algorithms is equivalent to assume that each driver is capable to find the best route, according to network structure. This in turn means that drivers take advantage at maximum of road network resources. Therefore using SPs as routing algorithm allow us to consider the maximum level of serviceability from driver's perspective. Criticality measures would then account for the drop in this level of serviceability due to the removal of the network element we are considering.
Therefore SP-based centrality measures, weighted with traffic demand and on grounded on a detailed description of network structure, offer a valuable insight of network criticality, assessing the contribution to vulnerability of road network elements, even in urban areas. Furthermore it allow us to depict a criticality picture of the whole network as they're quite easy to calculate.

Taking advantage of a huge data-set of Floating Car Data from vehicles moving in the Rome urban area we estimate traffic demand in terms of zone aggregated OD matrices. We propose two criticality index that account for different aspects of road network vulnerability. In order to compute in a reasonable time criticality indexes we perform a Monte Carlo approximation and describe its computational implementation. Finally we produce criticality maps of the Rome road network.
Our work presents many innovative aspects: we firstly introduce a new method to calculate criticality indexes of urban street network, making use of the topology and GPS traces from a large scale floating car fleet. We also introduce an original centrality measure with a very effective and practical meaning. Finally we produce criticality maps of the urban street network.
The paper is organized as follows: in Section 2 we present the case study data sources used to estimate the

indexes as well as the pre-processing operations applied in this study, in Section 3 we define and discuss centrality measures we used, in Section 4 we show the results while in Section 5 we critically discuss our methods, suggesting further development of our research.

2. CASE STUDY DATA

Our work relies on three different information layers: a graph representation of the road network, a geographic map of the urban area on which we implement a zoning routine and GPS traces collection of a large scale floating car fleet.
The Tele Atlas MultiNet map database of Rome was used in our study as it offers a highly accurate reproduction of the street network. The database contains a directed graph $G=(V,A)$, where V is the set of nodes and A the set of directed edges (arcs), composed of $|V|=205567$ nodes and $|A|=432405$ arcs.
Each road segment contains several attributes on the functional road class, the direction of traffic flow (one-way, two-way, divided highway), the number of running lanes, the traffic free flow speed, the restricted maneuvers, etc.. One of these attributes is the Net2Class classification and is defined here because it is especially relevant for this study. Net2Class represents a classification of seven networks of roads and ferries, based on their importance, where each forms a connected graph together with the higher Net2Class(es). So, the Net2Class is a kind of importance classification or hierarchy of connected road segments (freeway, motorway etc.) (Figure 1).

Figure 1: Tele Atlas MultiNet graph up to Net2Class=3 in the city of Rome. Color scale varies from blue to red according to the Net2Class index. Red streets are more important than blue ones as they exhibit lower Net2Class score. The urban street network of Rome is built on a metropolitan freeway that surround the city, (Grande Raccordo Anulare or GRA) which correspond to the big red circle in the figure, and some other fast streets connecting GRA to the city center.

We assign a travel cost $t(e)$ to each link e defined as the time needed to cross it at a speed equal to the speed limit (the ratio between link length and its speed limit).
We subdivide the study area into 136 zones (Figure 2) by applying a zoning routine (Zheng, 2012) taking into consideration the road segments with a net2class value lower than 3.

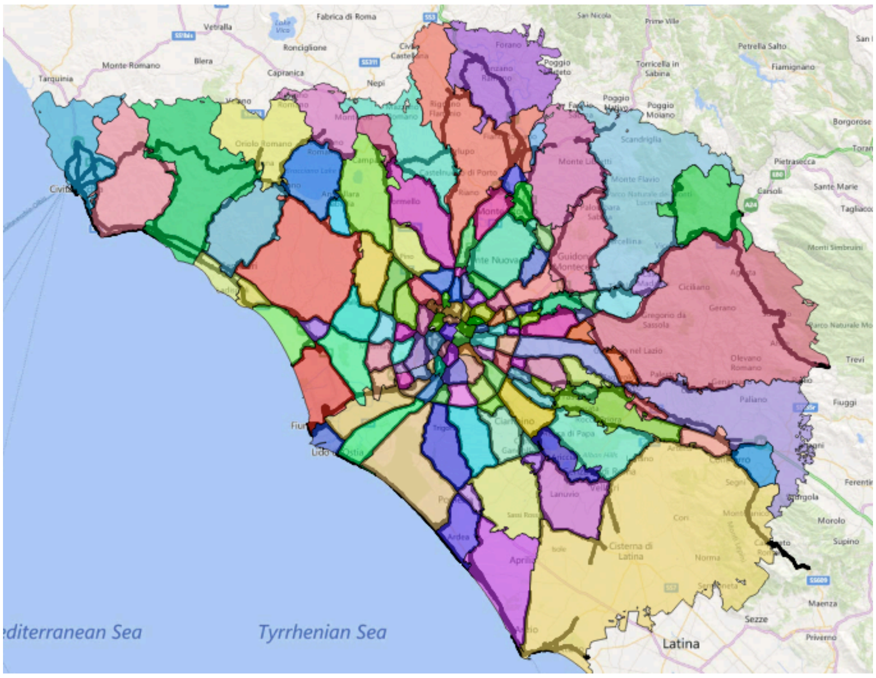

Figure 2: Area zoning outcome

A large Floating Car Data Collection is used in our study to extract the vehicular travel patterns in the study area. The Floating Car Data system, operated by OCTOTelematics, is built up of a large fleet (approximately 8% of the vehicle fleet in Roma) of privately owned vehicles equipped with an on-board unit (OBU) that stores GPS measurements (position, heading, speed, quality) and periodically transmits them to the Data Processing Center (DPC). Each OBU integrates the following components: a GPS receiver, a GPRS transmitter, a 3-axis accelerometer sensor, a battery pack, a mass memory, a processor and RAM.

We associate to each start and stop position the zones to which they belong to. We divide the days of the week in six time slots (0-6, 6-9, 9-12, 12-16, 16-20, 20-24). We have $7*6=42$ time slots, six for each day of the week. A trip belongs to a time slot if at least $2/3$ of its duration is inside it. We are then able to calculate the zone aggregated OD (Origin-Destination) matrices T^t on each daily time slot t.

3. CRITICALITY INDEXES

We define criticality indexes (CI) by rearranging centrality measures in graph theory (Newmann, 2010), particularly stress centrality and efficiency centrality. The basic ingredients of these measures are the shortest paths connecting each node couple in the graph.
Let (u,v) be a couple of nodes of the graph, $u \neq v$. The shortest path (SP) $\Pi(u,v)$ connecting them is defined as the ordered sequence of nodes $(u, n_1, n_2, \ldots, n_{n-1}, v)$ such that u and $n_1, \ldots, n_i$ and n_{i+1}, n_{n-1} and v are adjacent $(i=1,\ldots,n-2)$ and the cost of the path $\sum_{k=1,\ldots,n} t(e_k)$, where e_k is the link connecting two adjacent nodes, is minimum.
SPs depend both on the adjacency matrix of the resulting graph and the links costs in terms of travel times by using speed limits that best reflect the character of the road. Therefore SPs and in turn centrality indexes depend uniquely on the network structure and its physical characteristics.
In order to consider traffic demand the weight of each SP $\Pi(u,v)$ is given by a coefficient $p^h(u,v)$ that represents the probability to observe a trip from a node u to a node v in the time slot h. As our data set is too sparse to calculate them directly we estimate $p^h(u,v)$ starting from zone aggregated OD matrices, reasonably assuming that given a trip starting (or ending) in a zone Z (Z') each node of Z (Z') is equally likely to be the

origin (destination) node of the trip.. Let then $f^h(Z,Z')$ be the experimental probability to observe a trip starting in Z and ending in Z' during time slot h. $f^h(Z,Z')$ is therefore an element of the zone aggregated OD matrix. Then for each node couple (u,v) such that $u \in Z$ and $v \in Z'$ we set:

$$p^h(u,v) = \frac{f^h(Z,Z')}{|Z||Z'|} \tag{3.1}$$

where $|Z|$ is the number of nodes in Z (if $Z=Z'$ we use $|Z'|-1$ instead of $|Z'|$).
By combining these two elements (SP and probability coefficient) we calculate CIs.
Therefore our indexes take into account network structure and architecture, through SPs, and traffic demand as we weight each path with the $p(u,v)$.
In what follows we define each index and discuss it in detail. For clarity reasons will omit the superscript h pointing out that CIs are calculated in each time slot, by modifying transition probabilities.

3.1 Stress Centrality

The most intuitive way to calculate criticality of an arc is to estimate how many paths pass through it. Stress is an expression of this intuition.
Let $e \in A$ be an arc of the network. We define the stress $S(e)$ of the arc e as:

$$S(e) = \sum_{u \in A, v \neq u \in A} p\ (u,v)\delta((u,v),e) \tag{3.1.1}$$

where:

$$\delta((u,v),e) = \begin{cases} 1, & if \quad e \in \Pi(u,v) \\ 0, & otherwise \end{cases} \tag{3.1.2}$$

The notice $e \in \Pi(u,v)$ means that the node couple connected by e is part of the $\Pi(u,v)$.
$S(e)$ is actually a rearrangement of stress centrality (Newmann, 2010) that measures the number of SPs weighing on a network element. Therefore an arc has an high stress centrality if many SPs pass through it. According to our definition each path has a different weight in the computation according to the probability $p(u,v)$. Of course $S(e) \in [0,1]$ where the lower bound is assumed when no path with positive probability transverse e and the upper bound is reached if all the paths with positive probability pass through e.
Arcs can exhibit a high levels of stress if a huge number of SPs with low probability traverse them or if they are interested by a relatively low quantity of SPs with a high probability or in a mixed situation. In every case, if we consider the fastest routing strategy, a big portion of traffic volume is routed on these arc and they're therefore critical for the network connections.

3.2 Importance

Let's now consider the interruption of an arc (because of disruption, traffic jam, rainfalls etc.) so that it cannot be traversed. As stated in (Jenelius, 2006) we can measure the degree of criticality of an arc by computing the effect of its inaccessibility in terms of increasing travel cost. This measure in turn is inspired by efficiency centrality (Newmann, 2010)
Let $t(u,v)$ be the travel cost (i.e. time) of the SP $\Pi(u,v)$ and $t^{(e)}(u,v)$ the travel cost (i.e. time) of the SP $\Pi^{(e)}(u,v)$ which is the SP connecting the node couple (u,v) avoiding the arc e.
Of course $t^{(e)}(u,v) \geq t(u,v)$ because of the definition of SP. We therefore define the importance $I(e)$ of the arc e as:

$$I(e) = \sum_{u \in A, v \neq u \in A} p(u,v)\beta((u,v),e) \tag{3.2.1}$$

where

$$\beta((u,v),e) = \frac{(t^{(e)}(u,v) - t(u,v))}{t(u,v)} = \frac{t^{(e)}(u,v)}{t(u,v)} - 1 \tag{3.2.2}$$

represents the fractional increasing of travel time due to the removal of the link *e*.
It is clear that $\beta((u,v),e) \geq 0$ and equality holds if $t^{(e)}(u,v)=t(u,v)$, i.e. $\Pi(u,v)$ doesn't pass through *e* or it interest *e* but is equivalent, in terms of travel cost, to $\Pi^{(e)}(u,v)$. The higher is β the higher is the travel time of the path that avoid link *e*, with respect to the SP on the network including *e*. Weighting β by p allow us to weight differently paths that represent different portion of traffic volume.
High importance values of an arc imply that, even if we reroute the journeys from the beginning, the average travel time increase a lot if we exclude the arc from the network. Therefore arcs with a high importance are critical: the network doesn't present reliable alternatives that could satisfy efficiently traffic demand.

4. RESULTS

Each CI is calculated through a Monte Carlo approximation (Metropolis, 1949) by extracting a sample of representative path according to (3.1). CI are then related to each network arc. We can create a criticality map by simply coloring each arc according to its criticality score.
All of the figures showed in this section regards the time slot from 6 to 9 a.m. during the weekday of Monday. Color scale ranges from blue to red according to criticality (blue arcs are less critical than red arcs).
In this time slot many people living in the suburbs travel to downtown to reach their work place. Therefore, as we can see in Figure 3, the South-Eastern part of the GRA and other internal freeways are the most stressed as they represent the fastest way to connect suburbs to downtown. The high street density in the city center implies that corresponding arcs are not highly stressed as the paths tend to spread uniformly on them.
Nevertheless many internal streets show high Importance values (Figure 4). These implies that their removal produce an high increase on the average travel time, even if their not traversed by many paths.
In order to understand the behavior of the importance score let's look at a detail of the importance map (Figure 5). As we can see Important streets are those fast street that connect different areas with a very high arc density: they actually represents bridges between different zones of the city.

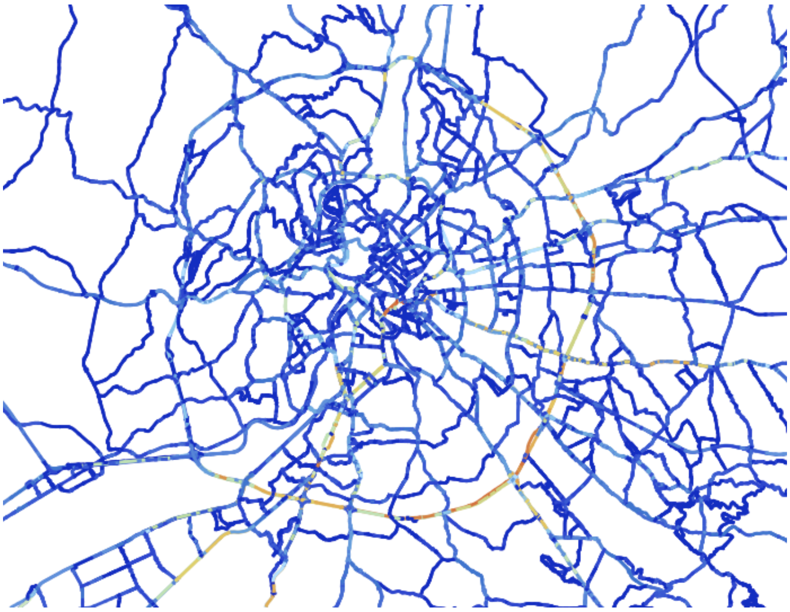

Figure 3: Stress Centrality Map during 6-9 time slot on Mondays.

Figure 4: Importance Map during 6-9 time slot on Mondays.

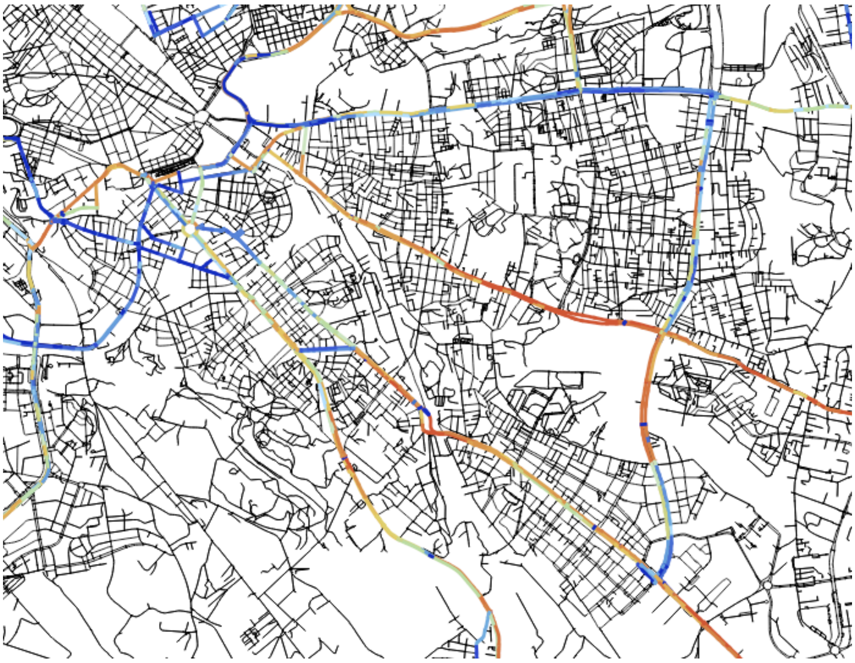

Figure 5: A detail of the Importance map. The black lines correspond to the whole street network.

5. CONCLUSIONS

In this paper we define and calculate criticality indexes of urban street network by combining its structural properties and traffic demand.

We first implement a routine to identify urban zone, starting from the principal street infrastructure. We calculate zone aggregated OD matrices from our Floating Car dataset. Each criticality index is then estimated by generating a number of shortest paths connecting two nodes extracted according to time dependent OD patterns.

Each measure we consider highlights a particular aspect of arc criticality. Stress centrality depends on the number of SPs passing through an arc. The effect of removing an arc from the network is considered by Importance and Uninformed Importance. They measure the average increase of travel time produced by the removal of an arc. Therefore arcs with high Importance values guarantee an efficient communication as its removal causes a significant growth of travel time. Particularly, we introduce Uninformed Importance in order to mimic a situation where drivers are not aware of the blocking and should find a new route to reach their destination. This represents a more realistic case than the one considered by Importance.

These measures are then used to draw criticality maps of urban street network on a GIS platform. These maps represent a very useful and intuitive tool for city planners and other decision makers in order to prevent problematic situation and address efforts to solve them. Building new streets, forecasting, preventing and facing emergency situation, smartly maintaining the road network are just some of the task that our maps can help to reach.

Current research is focused on strengthening our computational methods in order to obtain more reliable and stable results.

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