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Transportation Research Procedia 27 (2017) 857–864

Transportation Research Procedia

www.elsevier.com/locate/procedia

20th EURO Working Group on Transportation Meeting, EWGT 2017, 4-6 September 2017, Budapest, Hungary

Estimating travel time reliability in urban areas through a dynamic simulation model

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Abstract

It has been recognised that travelers do not only take travel time into account, but also travel time reliability (TTR). In the presence of travel time unreliability, travellers typically allow more time for their trips in order to limit the possibility of arriving late. This extra time allowance could be reduced increasing transport reliability, with a clear user benefit. Therefore, the evaluation of TTR has been receiving considerable attention in recent years, also in consideration of the current availability of real-time data. This study proposes a methodology for estimating TTR of an extended road network, through the calibration of empirical relations and the finding's representation on GIS maps. The basic variables used are travel times of each link belonging to the network, estimated through a traffic model, combining dynamic assignment with rolling horizon technics and real-time traffic measures from radar sensors. Different statistical measures are used to analyze the quality of the database and its usefulness for monitoring and quantifying TTR, such as Standard Deviation, Coefficient of Variation (CV) and Congestion Index (CI). The methodology is applied to the urban area of Catania (Italy) and three levels of analysis are performed: a Single Link Analysis, a Multi-Link Analysis and a Global Network Analysis. Empirical relations between CV and CI are found and will be used in the appraisal of transport network's performances based on TTR. This work concludes discussing how the process for estimating TTR, as a short term measure, can be attained in urban conditions.

Peer-review under responsibility of the scientific committee of the 20th EURO Working Group on Transportation Meeting.

Keywords: Travel Time Reliability; Dynamic traffic model; Road urban transport network; Intelligent Transport Systems, GIS; Congestion Index

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2352-1465
Peer-review under responsibility of the scientific committee of the 20th EURO Working Group on Transportation Meeting.
10.1016/j.trpro.2017.12.134

1. Introduction

Changes in commerce and personal lifestyles have increased the importance of a reliable transport system. Passenger movements, both for business and social purposes, have become more complex with changing patterns of employment, increased disposable income, recreational choices and leisure time. These diverse and geographically-spread activities have led to more intensive use of transport systems, bringing greater dependence on transport network to be reliable. For this reason, travellers' choices (hour of departure, destination, mode and paths) are not affected only by the experienced average travel time, but also by its variability through the perception of travel time reliability (TTR). Actually, travel time is an effective factor for measuring transport network performances and its efficiency. It varies over time on a given road link and it is influenced by a variety of factors that lead to congestion. (Lomax et al., 2003). Accordingly, when travel time is affected by high level of variability, travellers typically allow more time for their trips in order to reduce the possibility of arriving late at their destination. Reducing unreliability means that this extra time allowance could be decreased or avoided completely, presenting a clear user benefit (Torrisi et al., 2016).

The first step to recognising the importance of reliability is to monitor it. Thus, a methodology is proposed to estimate travel time reliability on an extended urban road network, at different aggregation levels, by using historical radar-detector data and a real-time traffic simulation model, through the calibration of empirical relations and the findings' representation on GIS maps with different layers.

The remainder of the paper is divided into six sections. Section 2 provides a review of TTR definitions in the general context of transportation and discusses the importance of using different performance indicators to evaluate travel time reliability. Section 3 describes the methodology identifying the significant empirical relations among the model variables. Section 4 presents the case study with a description of the territorial framework and the analysis of the data for the model development. Section 5 shows the modelling results and section 6 concludes the paper by summarizing the main findings and directions for further development of the research.

2. Travel rime reliability definitions and performance indicators

In a review of literature on transport reliability, it was found that TTR can be defined in a number of different ways. The choice of definition is important because it has major implications for policy. Technically, a reliable system is one that performs its required functions under stated conditions for a specified period of time. An alternative definition of reliability draws on the attribute of predictability. In this context, a congested road system where the travel times at different times of day and different days of the week are consistent, and hence predictable, would be ranked as highly reliable (OECD, 2010). Thus, a road network is reliable as long as travel times are consistent, even if the network underperforms due to regularly-slow speeds caused by traffic congestion. While both interpretations are valid, this study focuses on the second one. The key aspect is the assumption that network users have an expectation of a particular level of service and that reliability is a measure of the extent to which the traveller's experience matches his expectation (Hellinga, 2011). In other words, reliability is equivalent to the predictability of travel times and, from the perspective of a traveller, it is associated with the statistical concept of variability. According to this definition, a reliable road network has consistent performances and network users are more bothered by reliability as travel time becomes more uncertain. In fact, users have deeply negative perceptions of unexpected delays because such delays have larger consequences than drivers face with everyday congestion. Travelers also tend to remember the few bad days they spent in traffic, rather than an average time for travel throughout the year (Fig. 1).

Traffic conditions in the past have often been communicated to travelers only in terms of simple averages (left chart in Fig. 1). However, as said just before, most travelers experience and remember something much different than a simple average of commuting travel time (right chart in Fig. 1).

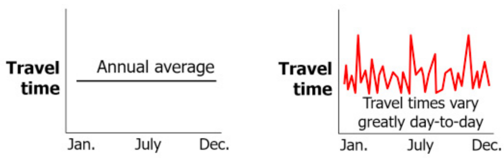

Fig. 1. Travelers' perception of traffic conditions (OECD, 2010)

Therefore, it is important to quantify TTR. Research findings suggest that the evaluation of route travel time characteristic are key reliability indicators on road networks (Lo, 2002; Cassir et al., 2001). The user perspective considers specific characteristics of travel times and how he may response to prevailing reliability levels. From this point of view, related performance indicators are the standard deviation, the variance, the range, the percentiles and derived measures such as the buffer index (OECD, 2010).

Recent years have seen a growing interest in monitoring and estimating TTR on urban transport networks and developing methods to measure and evaluate it (Carrion and Levinson, 2012; Emam and Al-Deek, 2006; Taylor, 2013). Acknowledging the effects of congestion on travel time variability, many studies have attempted to measure TTR in order to present average conditions and indications of how often and/or how much travel time varies over time. Arup (2003) estimated a relation between travel time reliability and congestion, based on the observation that variability is likely to be greater as flows reach capacity. He used the so-called congestion index (CI) as a key explanatory variable of variability, and the coefficient of variation (CV) to measure the reliability or variability of travel time, estimating a relation between the two coefficients. From reports, it was noticed that there was a tendency for the journey CV to increase with the CI and to decline with journey length. As shown in the study by Shi and Abdel-Aty (2015), the benefits of Big Data technologies such as loop detectors include direct and indirect applications to analyse the interrelation of congestion and travel time reliability. On this basis, the evaluation of travel time reliability (TTR) has been receiving considerable attention in recent years, also in consideration of the current extraordinary availability of real time traffic data from sensors, floating car data and traceable personal mobile devices (Torrisi et al., 2016). Following these remarks, the methodology on which the study is focused is described in the next section.

3. Methodology

The methodology concerns the estimation of travel time reliability of an extended road network at different aggregation levels, through the empirical relations of traffic data and the findings' representation on GIS maps with different layers. As stated in section 2, a review of existing reliability indicators suggests that governments have started monitoring and targeting reliability. Specifically, the statistical measures which have been used to quantify TTR are Standard Deviation, Coefficient of Variation and Congestion Index.

Standard Deviation represents a useful indicator in situations where there is a need to look at the variability in travel times around an average value and it is expected that this variability is not much influenced by extreme delays, the travel time distribution will be not very much skewed (Bates et al. 2001; Lomax et al. 2003). It can be calculated as shown in Eq. (1):

$$\sigma = \sqrt{\frac{1}{N-1}\sum_1^N (TT_{d,i-j} - TT_m)^2} \tag{1}$$

where σ is the standard deviation, N is the number of travel time observations in a particular time of day or day of week period, $TT_{d,\,i\text{-}j}$ is a travel time observation on day d during time interval i-j and TT_m denotes the mean travel time.

The Coefficient of Variation, i.e. the ratio of standard deviation to the mean travel time, represents the variability of travel time and it is calculated with the Eq. (2):

$$CV = \frac{\sigma}{TT_m} \tag{2}$$

The Congestion Index gives model-users a simple way of generating travel time variances from standard data that already exists on mean travel times. It is defined as the ratio of the mean travel time to the free flow travel time for a journey or link, as represented by the Eq. (3):

$$CI = \frac{TT_m}{TT_{ff}} \tag{3}$$

where TT_{ff} is the free flow travel time.

The basic variables used are travel times of each link which belongs to the network, estimated through an assignment traffic simulation model (Meschini and Gentile, 2011), periodically updated by real time traffic data through the "rolling horizon" technique, as proposed by Mahmassani (2001), to reproduce the dynamic interaction between the level of congestion and users route choices of a congested road network.

This research accomplishes a full range of sizes and aggregation levels of the transport network. Therefore, three type of analysis were implemented: a Single Link Analysis (SLA) which is based on data for individual links; a Multi-Link Analysis (MLA) which utilises journeys covering a number of links and a Global Network Analysis (GNA) which considers all the links that belong to the analyzed network.

First, N sets of links indexed k = 1, …, N were analysed. It was assumed that estimated travel times were representative of the corresponding link for each time interval $i-j$ during a day d. The simulation model aggregates traffic data in 15-min intervals to obtain stable values. As a result, each day was divided into 96 time intervals and indexed as i= start of time interval and j= end of time interval. Further, $t_{k,d,i-j}$ is defined as the average travel time at link k on day d during time interval $i-j$. An array of travel times, symbolised by $T_{d,i-j}$, was constructed for each time interval $i-j$ for all analysed days through the sum of these travel times $t_{k,d,i-j}$, featuring the average total travel time of the considered traffic network, or path or link, as shown in the Eq. (4):

$$\mathrm{T_{d,i-j}} = \sum_{\mathrm{k=1}}^{\mathrm{N}} \mathrm{t_{k,d,i-j}} \tag{4}$$

The recommended form of the applied model (Arup, 2003) estimates the CV from CI term for each day d and time interval i-j in the urban area using the following formulation (Eq. 5):

$$CV_{d,i-j} = \alpha\ CI_{d,i-j}^{\beta} \tag{5}$$

where α is a constant or scale factor and β is the elasticity or coefficient for congestion index. The scale factor α is a number which scales, or multiplies the CI depending on the travel time variances from mean travel times. Hence, in the Eq. (5) it is the scale factor for CI or its coefficient and so it may be considered a constant of proportionality of CV to CI. Whereas, the elasticity coefficient β indicates the degree of variation of the two related variables CV and CI. They must be appropriately calibrated to produce more robust TTR relations using the widespread traffic data across the entire network. In more detail, these two variables are identified by minimizing the total square deviations between the measured and the calculated values of CV.

4. Case study

4.1. Territorial framework and data description

Catania is a city of about 300.000 inhabitants and it is located in the eastern part of Sicily; it has an area of about 183 km2 and a population density of 1.754,54 inhabitants / km^2. It's part of a greater Metropolitan Area (750.000 inhabitants), which includes the main municipality and 26 surrounding urban centers, some of which constitute a whole urban fabric with Catania (Ignaccolo et al., 2017). The main city contains most of the working activities, with a high commuting phenomenon and this has led to a heightened inclination to private mobility with the direct consequence of traffic congestion that greatly affects the network reliability.

The basic variables used are travel times of each link which belongs to the considered traffic network. They were obtained by the traffic supervisor centre operated by the Department of Civil and Architecture Engineering of Catania's University, where real-time sensor traffic data are combined with simulated traffic data (more details can be found in Torrisi et al., 2016 and Torrisi et al., 2017). Data have been simulated with 15 minutes' time intervals, so the amount of data is huge and a very precise information can be extracted from them. Because computations are referred to time interval of one hour, simulated traffic data of each 15-min are aggregated and the general form of the proposed model coincides according to this following Eq. (6):

$$\mathrm{T_{d,i-j}} = \frac{\sum_{\mathrm{k=1}}^{\mathrm{N}} \mathrm{t_{k,d,i-j}}}{\mathrm{n}} \tag{6}$$

with n = 4 which represents the number of simulation during the time interval of one hour.

These computations refer to traffic data of two weeks, taking into account both working days and non-working day. It was also carried out an analysis on day-to-day travel time variations and on with-in day variations.

For the global level of analysis, i.e. Global Network Analysis (GNA), the study area is shown in Fig. 2. The simulated road network is represented by the red graph and it is composed by 8763 links. The Multi-Link Analysis (MLA) concerns the comparison of two short paths (characterized by a sequentially set of links) with similar length but different location: Corso Italia situated in the city centre of the urban area and Viale Marco Polo in the peripheral zone (Fig. 2). Some of their specific characteristics can be found in Table 1. For the Single Link Analysis (SLA), we examined 49 arcs coinciding with those characterizing the two paths of the previous analysis.

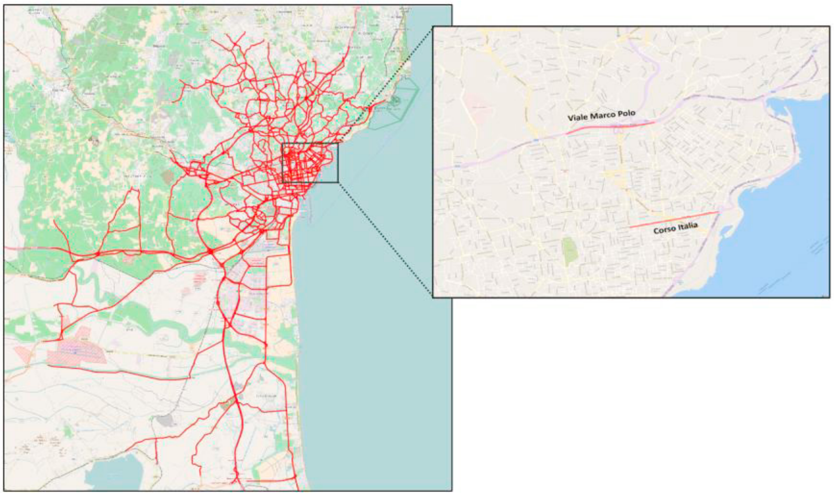

Fig. 2. Study area and simulated road network: Global Network Analysis (GNA) and Multi-Link Analysis (MLA)

Table 1. Characteristics of selected routes

	Corso Italia (1061 m)			Viale Marco Polo (1262 m)		
	Average	Minimum - Maximum		Average	Minimum - Maximum	
Length (m) of links	44,2	12	106	54,8	6	208
Average speed (km/h) in the links	27,7	4,1	49,7	27,2	14,1	29,9
Number of links	25			24		

4.2. Model development

Firstly, for every link, route or for the entire network, for each day of analysis, for each time interval, we calculate the standard deviation of the travel time, the mean travel time and the free flow time in order to calculate the respective coefficients of variation and congestion indexes.

Subsequently, the Single Link Analysis (SLA) examines the relationship between congestion and TTR on an individual link basis before examining journeys traversing more than one link. The relationship between CV and CI is estimated for every link k of the dataset and for each day d and time interval $i-j$ as follow (Eq. 7):

$$CV_{k,d,i-j} = \alpha\, CI_{k,d,i-j}^{\beta} \tag{7}$$

For the calculation of the CI (the ratio of actual time to minimum or 'free flow' time) two times are required: an average travel time for a period; and a reference travel time (or 'free flow' travel time). The reference travel time is the travel time that could theoretically be achieved when traffic is free flowing. This is usually less than the speed limit in order to allow for slowing down at junctions and other alignment features. The reference travel time for each link has been derived from the average travel time using the records collected between 00:00am and 06:00am.

The second analysis, undertaken for journeys comprising more than one link, i.e. Multi-Link Analysis (MLA) extends the SLA to journeys (comprising more than one link). The hypothesized relationship between CV and CI for the route r and for each day d and time interval $i-j$ is expressed from the Eq. (8):

$$CV_{r,d,i-j} = \alpha\, CI_{r,d,i-j}^{\beta} \tag{8}$$

Similar to the SLA, the reference travel time for each set of journeys has been derived from the average travel time collected between 00:00 and 06:00. Finally, the last one analysis, the Global Network Analysis (GNA) is extended to the entire analyzed network, applying these formulations to all the links that belong to it.

5. Results

5.1. Route elasticity using aggregated single link data

By referring to the SLA and MLA, the empirical relationships between CV and CI have been appropriately calibrated through the recognition of the scale factors α and the coefficients for congestion index β. Their identification was carried out, by setting as the objective function the minimization of the total square deviations between the measured and the calculated values of CV. The same procedure was applied to single links and to all links in a route aggregated. It occurs almost always that the route CI elasticities are lower than the single link CI elasticities.

Because of the uncertainty that travellers predominantly have to deal with is the day-to-day travel time variations (variations in travel time when departing at the same time each day), the following results focuses on day-to-day analysis. The relationship between CV and CI for the two analyzed routes is depicted in Fig. 3: in both cases, the calculated values with the aforementioned relationship, i.e. Eq. (7), are closely matching those measured, obtained by direct computations based on travel times given by the traffic simulation model. The estimated CI elasticity hires the values of 31.6 for Corso Italia and 44.6 for Viale Marco Polo, whereas the constant is slightly more than zero and precisely equal to 0.0091 and 0.0076.

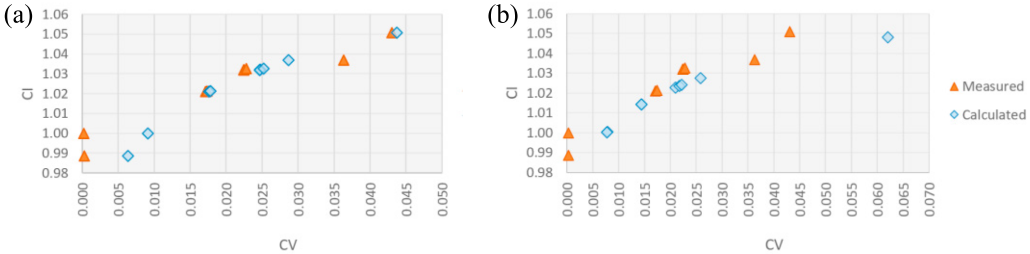

Fig. 3. Relationship between CV and CI: (a) Corso Italia; (b) Viale Marco Polo MLA

The elasticities are graphically compared for the two routes (Fig. 4). Along the horizontal axis are coefficients of variation calculated with the form of the model that estimates the CV from CI; whereas along the vertical axis are congestion indices calculated with Eq. (3). The regression curves that interpolate these spots are represented in red colour. It is important to specify that this study did not attempt to compare the estimated coefficients with other studies as these values strongly depend on the outlier criterion used, on the way the variation of expected travel time is taken into account and on the period over which the data is averaged. For this reason, the analysis has aimed at finding the best functional forms of the empirical relations for our database. Both datasets have been fitted with different type of regression: linear, second-degree and third-degree polynomial regression lines. By referring to the obtained results, the type of regression that better fits our data is the third-degree polynomial regression.

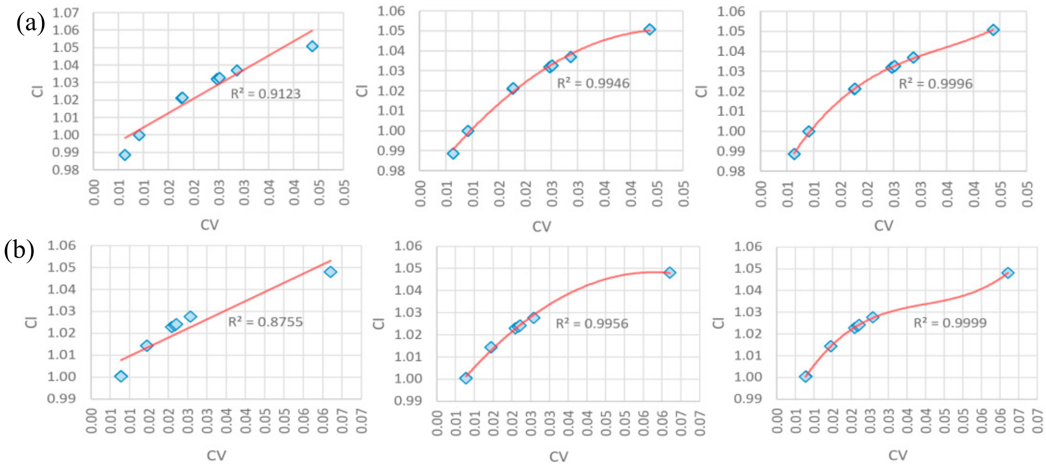

Fig. 4. Comparison of different regressions: linear, polynomial (n=2) and polynomial (n=3). (a) Corso Italia; (b) Viale Marco Polo

The specification of the mathematical equations associated to each regression form are synthetized in Table 2. The coefficients of determination R2 are well above the value of 0.7, and this indicates that the three regression lines approximate the real data points in a satisfactory way. In particular, for both routes the third-degree polynomial regression has a coefficient R2 close to unity, reaching the value of 0.999.

Table 2. Route Elasticity Findings based on Average Link CV and Average Link CI

Type of regression	**Corso Italia**		**Viale Marco Polo**	
Linear	$y = 1.6447x+0.9877$	R^2=0.9123	$y = 0.8366x+1.0012$	R^2=0.8755
Polynomial (n=2)	$y = -36.203\ x^2+3.4033x+0.9705$	R^2=0.9946	$y = -18.732\ x^2+2.1688x+0.9855$	R^2=0.9956
Polynomial (n=3)	$y = 1314.8x^3-134.72x^2+5.4661x+0.9594$	R^2=0.9996	$y = 696.26x^3-83.612x^2+3.6558x+0.9768$	R^2=0.9999

5.2. GIS map representation of network's TTR

The previous paragraph showed the results of the estimate route elasticity using aggregated single link data. The same methodology was applied to the third aggregation level, i.e. GLA, focusing on the same traffic variables. This analysis was performed by using average performance indicators calculated starting from the simulated travel time of each individual link. Thus, it is possible to globally describe the characteristics of the network.

The urban road map of Catania is represented by a graph characterised in a chromatic scale (shown in Fig. 5). Each link corresponds to a coloured line determined according to the value of mean travel time expressed in seconds per meter (on the left side) and to the value of congestion index (on the right side) during peak hours. This representation illustrates how the network's performances change over time. It is immediately clear as the average travel times are not representative in the case we consider the operational features of the network during peak hours. Results show that the mean travel times have the higher values fairly widespread in the central urban area of Catania, where the congestion phenomenon is achieved more frequently. Nevertheless, many links of the network that are characterized by a quite high average travel time but a lower congestion index enables network users to plan their travel accordingly a consistency in speed and travel time. More generally, when travel time on a link varies widely, the reliability is low. On the other hand, when all trips take more or less the same time, reliability is high. These outcomes indicate that it is possible to test the direct link between traffic congestion and TTR. That said, it is recognised that remedial actions directed at congestion can improve reliability and, similarly, actions that improve reliability can reduce congestion.

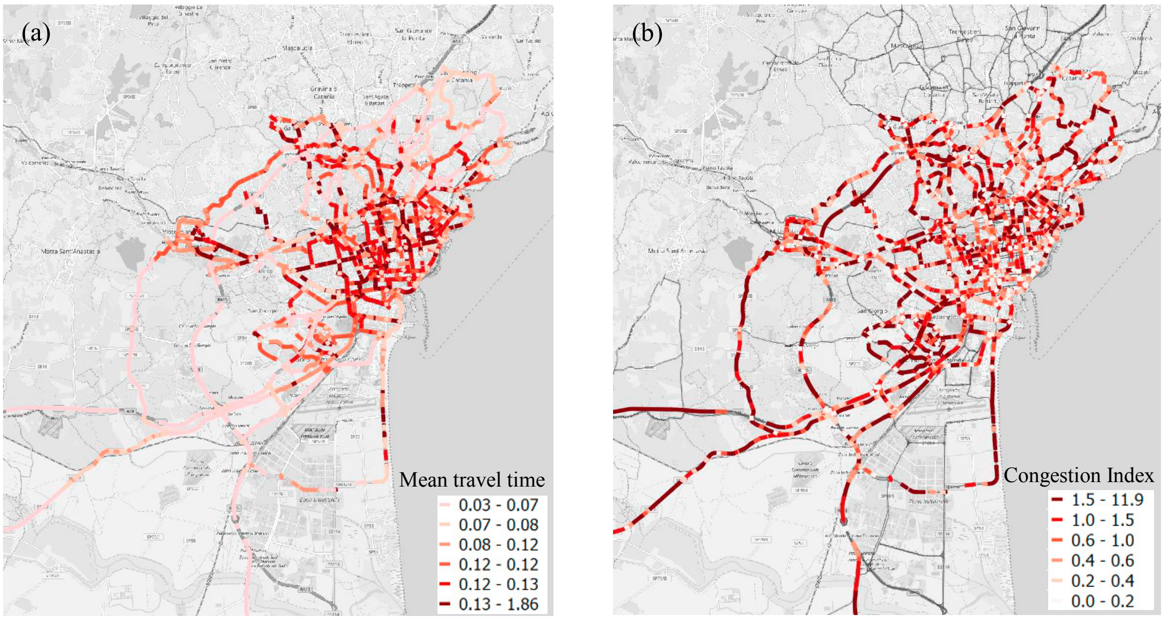

Fig. 5. Gis maps representation of network's TTR: (a) mean travel time; (b) congestion index (8:00am, working-day)

6. Conclusions

The evaluation of travel time reliability has been receiving considerable attention in recent years, and a robust and consistent assessment of network performances should be developed in order to ensure good level of reliability.

In this way, the paper proposes a methodology for estimating travel time reliability of an extended traffic network at different aggregation levels by using historical radar-detector data and a real-time traffic simulation model, through the calibration of empirical relations and the findings' representation on GIS maps with different layers. A database has been constructed comprising travel times for individual links of the analyzed network and it has been used to estimate TTR.

The statistical measures which have been used to quantify TTR are Standard Deviation, Coefficient of Variation and Congestion Index. The empirical relationships between CV and CI have been appropriately calibrated, in order to find the best functional form of the empirical relations for our database. GIS maps have been used to illustrate the network's results in a cartographic representation, that turns out to be more immediately understanding. In particular, colouring the map is a way of illustrating how networks' performances change over time.

In conclusion, the relations derived from this study will be used in the appraisal of transport network's performances. It is intended that the found functional forms are valid for our own data set. Accordingly, further research needs to be conducted whether the relationship between CV and CI could be applied in other urban areas. Additional surveys based on a similar undertaken analysis will allow to find an appropriately averaged version of the model, able to give estimates of TTV, as a short-term measure, in urban conditions.

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