Residual Entropy and Critical Behavior of Two Interacting Boson Species in a Double Well

Road network vulnerability analysis: case study considering travel demand and accessibility changes

Gregorio Gecchele
Atraki s.r.l.
Via A. Diaz, 4 37015 S. Ambrogio di Valpolicella (Verona), Italy
Tel. (+39) 45-6862581
E-mail address: gregorio.gecchele@atraki.it

Riccardo Ceccato, corresponding author
Department of Environment, Land and Infrastructure Engineering – Politecnico di Torino
Corso Duca degli Abruzzi, 24 10129 Turin, Italy
Tel.: (+39) 011-0905616
E-mail address: riccardo.ceccato@polito.it

Massimiliano Gastaldi
Department of Civil, Environmental and Architectural Engineering – University of Padua
Via F. Marzolo, 9 35131 Padua, Italy
Tel.: (+39) 49-8275574
E-mail address: massimiliano.gastaldi@unipd.it

Abstract

Road network vulnerability analysis is helpful in the improvement of vulnerable links with proper maintenance investments and management strategies. This paper addresses issues that received limited attention in past studies: the estimation of travel demand after the link disruption, and the analysis of accessibility variation. An Activity-Based Model was used to estimate travel demand changes due to link closure, and link importance is evaluated with a set of vulnerability indicators; accessibility changes induced by link closure are presented and discussed. The vulnerability analysis has been conducted to the road network of the municipality of Dolo, northern Italy. Considering spatial distribution of activities and trips, results obtained with Activity-Based Model are more reliable than those obtained with Fixed Demand Model, which has unrealistic assumptions of unchanged travel demand after network degradation. These findings are relevant for appropriate resource allocation strategies, which

depend on correct link vulnerability analysis and ranking.

Introduction

Transportation networks are lifelines which support services essential to society, and need to be preserved in their functionality in case of disruptions caused by events which originate within (e.g. traffic accidents and technical failures) or outside the transport system (e.g. debris-flows, floods, earthquakes, storms, etc.). Authorities and agencies face the need to prioritize the allocation of (generally) limited resources to guarantee the proper serviceability of transport networks, and road networks in particular. For these reasons, network vulnerability has emerged as a significant field of research in transport analysis and planning in the past decade. Results of vulnerability analysis can be helpful in the improvement of vulnerable links with ordinary and extraordinary maintenance investments and proper management strategies.

According to several authors (Faturechi and Miller-Hooks 2014; de Oliveira et al. 2016; Reggiani et al. 2015), the vulnerability concept still lacks a consensus definition, and it depends on the application context (Caschili et al. 2015; El-rashidy and Grant-muller 2014). The first formalization of the concept in transport analysis can be found in Berdica (2002), who defines "vulnerability" as "a susceptibility to incidents that can result in considerable reductions in road network serviceability", where serviceability of a link/route/road network is interpreted as "the possibility to use that link/route/road network during a given period". Other concepts related to vulnerability are robustness and reliability (D'Este and Taylor 2003; Faturechi and Miller-Hooks 2014; de Oliveira et al. 2016; Reggiani et al. 2015; Rupi et al. 2015b): robustness focuses on the impacts of the disturbance (e.g. decrease of network performance), reliability focuses on the frequency of occurrence of the disturbance, that is on its probability. For other authors (Bono and Gutiérrez 2011; Husdal 2004; Luathep et al.

2011), reliability is a measure of network stability, and vulnerability should be a measure of the consequences of a network element collapse (or underfunctioning) (Cai et al. 2017; Faturechi and Miller-Hooks 2014).

In this paper the risk theory framework was adopted to represent degraded scenarios as a list of “triplets”, each consisting of a description of a particular scenario, the probability of that scenario occurring, and the impact of the scenario (Jenelius and Mattsson 2015).

The vulnerability analysis conducted in this research focuses on the assessment of network impacts produced by the disruption of a given element (a road network link), independently of the type of event and the probability of occurrence of such event.

Following past studies approach (Jenelius, 2009; 2010, Jenelius and Mattsson, 2015; Rupi et al., 2015b), the “importance” was used to measure the impacts of link disruption. In practice, link importance is commonly estimated with vulnerability indicators, which compare network performance before (current network) and after (“degraded” network) the link closure. The most common indicators are based on total system cost (often, the travel time) (Balijepalli and Oppong 2014; Carturan et al. 2013; Dalziell and Nicholson 2001; Dehghani et al. 2017; Guo et al. 2017; Hu and Ho 2013; Jenelius et al. 2006; Jenelius 2007, 2009, 2010, Jenelius and Mattsson 2012, 2015; de Oliveira et al. 2016; Rupi et al. 2015a, 2015b; Scott 2006; Taylor et al. 2006; Wang et al. 2016); others refer to accessibility measures (D’Este and Taylor 2001; Kermanshah and Derrible 2016; Lu et al. 2015; Miller et al. 2015; Taylor 2008; Taylor et al. 2006; Taylor and Susilawati 2012), connectivity (Scott et al. 2006; Zanini et al. 2017), topological measure of dispersiveness/concentration (Sakakibara et al. 2004), distance travelled, link flow and capacity (Balijepalli and Oppong 2014; Chen et al. 2012; Guo et al. 2017).

In the literature link importance is generally estimated with a vulnerability scan approach (Chen et al. 2012; El-rashidy and Grant-muller 2014; Knoop et al. 2012; de Oliveira et al. 2016; Scott et al. 2006; Wang et al. 2015), which consists in removing one link from the network, and analysing the effects using some vulnerability indicators. The analysis can be done for each link in the network (full-scan approach), or a subset of selected links, according to a set of criteria (partial-scan approach) (Cats et al. 2016).

In both cases, the literature review highlighted that the majority of authors adopted the inelastic (or fixed) demand assumption for traffic simulation (Balijepalli and Oppong 2014; Dehghani et al. 2017; Erath et al. 2010; Hu and Ho 2013; Jenelius et al. 2006; Jenelius 2007, 2009, 2010, Jenelius and Mattsson 2012, 2015; Kermanshah and Derrible 2016; Lu et al. 2015; Luathep et al. 2011; de Oliveira et al. 2016; Wang et al. 2016). This means that travel demand is independent of changes in network level of service and traffic models may represent route choice changes (detour), but changes in trip mode, destination or time period may not be considered.

Since disruptive events cause variations in travel demand (Kontou et al. 2017), this paper adopted an Activity-Based Model, which allows simulating users' responses to changes in network configuration, modifying travel demand according to spatial accessibility variations. These aspects have been considered in few studies (Chen et al. 2007, 2012; Dalziell and Nicholson 2001; El-rashidy and Grant-muller 2014; Guo et al. 2017; Miller et al. 2015; Taylor 2008) but still need to be developed and further analysed. Investigating the effects of Desert Road closure in New Zeland, Dalziell and Nicholson (2001) considered travel demand elasticity and assumed that some trips might not be performed if the increase of travel cost due to link closure exceed a certain value. In order to evaluate travel demand changes in detail, Taylor (2008) and Miller et al. (2015) used an Activity-Based Model, and Chen at al. (2007) and Du, Xiaowei and Cheng (2017) adopted a Combined Travel Demand Model. However, in these papers models were limited to a single link or few links analysis (Chen et al. 2007; Taylor 2008) or they were related to specific scenarios (such as earthquake damage scenarios (Miller et al. 2015)).

As stated by Reggiani, Nijkamp and Lanzi (2015), “transport is a largely derived demand, so that accessibility analyses, by including socio-economic elements, seem to be crucial for the study of the resilience/vulnerability impacts from transport networks to socio-economic-environmental networks”. Therefore, network degradation significantly affects users’ accessibility (D’Este and Taylor 2001). Unlike the classical definition of accessibility, which consider only characteristics on the supply side of a transportation system, Taylor (2008) adopted a combined measure which considers also the demand side and travel behavior of users. Fixed Demand Model is not suitable for such definition of accessibility, therefore Activity-Based Model was adopted by several authors (Miller et al. 2015; Taylor 2008).

According to this perspective, this paper extended previous studies investigating the roles of accessibility and travel demand changes in urban road network vulnerability, which have received limited attention in the past. In order to evaluate these variations this paper adopts an Activity-Based Model. The link importance is evaluated with a set of vulnerability indicators adopting a vulnerability scan approach. In order to define a general methodology, which can be largely adopted in any vulnerability analysis, no assumptions about the type and the probability of occurrence of the event which produces the link closure are considered. The Activity-Based Model evaluates accessibility and travel demand changes, and network performance produced by link closure, providing realistic and, therefore, solid and reliable results, which are useful to identify critical links. Moreover, by testing the proposed methodology on a real urban network in Italy, this paper contributes to perform vulnerability analysis for European case studies, which are very limited in previous works.

Material and methods

The vulnerability scanning approach was adopted to identify the most critical elements of the system, whose degradation had the largest impacts on accessibility and vulnerability indicators.

The basic scanning procedure follows these steps (de Oliveira et al. 2016; Taylor and Susilawati 2012):

Step 1. Compute the vulnerability indicators for the base scenario (current network). The Activity-Based Model is run to produce base travel demand (OD matrices) and network performance; accessibility and vulnerability indicators are calculated.

Step 2. Identify candidate critical links to evaluate. They can be all the links of the network (full-scan), or those for which there are ‘reasonable’ finite probabilities of use (partial-scan).

Step 3: Simulate the closure of each candidate link and compute the vulnerability indicators for each new scenario (degraded network). The Activity-Based Model is run on the degraded network generating modified travel demand (OD matrices) and network performance; accessibility and vulnerability indicators are calculated.

Step 4: Determine accessibility and vulnerability indicators’ changes, and identify the most critical links.

The same procedure has been applied with a Fixed Demand Model: the performance for degraded networks was calculated with the travel demand estimated in step 1. Results obtained with the two models are compared and discussed. Details about Activity-Based Model and performance indicators are presented in the following sub-sections.

Activity-Based Model

In transport systems, supply changes may induce travel demand variations; in order to simulate these effects, the vulnerability analysis has been conducted with an Activity-Based Model (ABM). This model focuses on individual choices, assuming travel demand as derived from the need to participate in activities (Scott 2006) and elastic (Ortuzar and Willumsen 2011), i.e. responsive to transport system changes (accessibility, in particular). The model framework is based upon the work of Bowman and Bradley (2005), who developed and applied an econometric activity-based microsimulation model for the Sacramento (California) Area Council of Governments. In particular the disaggregated model simulates full-day activity and travel schedule for each resident in the study area (Bowman and Bradley 2005). The implemented ABM can be subdivided in the following sub-models (Figure 1).

(1) The *Population Synthesizer* generates the population in the study area from detailed attributes of a sample of households and zonal characteristics (e.g. number of persons living in a traffic zone). This sub-model expands disaggregate sample data (such as gender, income, size) in order to match aggregate households' characteristics with an Iterative Proportional Fitting process (Bowman et al. 2006; Bowman and Bradley 2005; Ortuzar and Willumsen 2011).

(2) The *Activity and Travel Simulator* simulates long term households' choices (e.g. work and school location, number of cars owned) and personal daily activities, that is a sequence of tours and trips carried out by each person belonging to the synthesized population. Choices are simulated with a Nested Logit framework (Bowman et al. 2006; Bowman and Bradley 2005), according to population and accessibility characteristics (zonal characteristics and transport network levels of service). In

particular, first a car ownership model is run for each household, and then, the full day activity schedule is calculated for each household member according to the following structure of the Nested Logit: decision to travel or not, purposes, time period and intermediate stops of the tours, and, for trips thus generated, choices of destinations and mode.

(3) The *Trip Aggregator* sub-model produces Origin-Destination matrices (by purpose, by time period of day and by mode) conveniently aggregating daily activity lists into Traffic Analysis Zones (TAZ).

(4) The *Network Traffic Assignment* sub-model assigns Origin-Destination matrices to the network and produces link flows with a Deterministic User Equilibrium model. This model assumes that users have a perfect knowledge of network travel costs, that is users are informed of link closure before they schedule their daily activities.

(5) The *Accessibility* sub-model produces TAZ accessibility values (active and passive), to be used by the Activity and Travel Simulator. Accessibility depends on attractiveness measures (such as number of employees, students and retail outlets), network level of service (e.g. minimum travel time to reach a zone), trip attributes (time period of day, mode, purpose, away from or return to TAZ) and zonal characteristics (e.g. presence of toll parking). In particular, active accessibility considers the number of workplaces and commercial activities in TAZs that a person can reach (residents' perspective), and passive accessibility considers the number of residents in the TAZ (reachability of economic activities) (Cascetta et al. 2013; Papa and Coppola 2012).

The updated levels of service are iteratively used by the Activity and Travel Simulator, until the equilibrium is reached (i.e. when travel demand is consistent with network levels of service).

The ABM was implemented in Citilabs Cube Voyager transport software and it considers:

- 3 travel modes (Single Occupancy Vehicles, High Occupancy Vehicles, Walk)
- 4 time periods (AM-peak period, MD period, PM-Peak period, Off-Peak period)
- 6 trip purposes (Work, School, Work-Based, Intermediate Stop, At Home, Other).

Vulnerability and Accessibility indicators

The vulnerability analysis was conducted adopting a set of vulnerability and accessibility indicators, introduced in this section. Accessibility can be considered as a more complete and useful indicator for vulnerability, since it captures spatial importance variability by means of economic variables, allowing the analysis of individual, communities and demographic groups consequences and topological connectivity (Miller et al. 2015; Reggiani et al. 2015).

Difference in Mean Accessibility per Person (MAP)

Difference in Mean Accessibility per Person for a degraded network, generated from the original one by removing link e, was proposed by Taylor (2008) and Miller et al. (2015). This indicator is highly correlated to user’s need to participate in out-of-home activities and reflects the complex interaction between travel demand and supply. In particular it is defined as:

$$MAP^{(e)} = \frac{\frac{\sum_{s(e)} A_s^{(e)}}{s^{(e)}} - \frac{\sum_{s(0)} A_s^{(0)}}{s^{(0)}}}{\frac{\sum_{s(0)} A_s^{(0)}}{s^{(0)}}} \quad (1)$$

where

$$A_s = ln \sum_{d=1}^{D} e^{V_{s,d}} \quad (2)$$

$s^{(0)}$ and $s^{(e)}$ are the flows of persons in the time period considered in the analysis who make a trip in current and degraded network, respectively; d is the set of destinations that person s can reach from his/her own home; $V_{s,d}$ is the systematic utility, the mean or expected value of utility perceived by persons having a choice set *D*, which depends on individual, zonal, and network parameters derived from the *Network Traffic Assignment* sub-model through a Deterministic User Equilibrium model. In this paper, these parameters were: number of employees in each sector and TAZ, presence of toll parking, minimum distance and travel time to reach a destination, number and age of household members, total household income and owned cars, tour purpose and time period of day. Coefficients of utility functions differ according to 3 travel modes, 4 time periods of the trip, 6 trips purpose, 4 household income classes and number of household cars (greater or less than 0); therefore the number of utility functions adopted is 576. For example, for car travel mode, AM – Peak period, work trip purpose, household income less than 33400 $ and more than 0 household cars, the utility is calculated as (Bowman and Bradley 2005):

$$V_{s,d} = -0.03t_{o.d} - 0.25d_{o,d} - 0.25toll_d \quad (3)$$

where $t_{o.d}$ and $d_{o,d}$ are the minimum distance and travel time to reach a destination, respectively; $toll_d$ is the parking toll. Observing Equation 3 one can note that all coefficients are negative, reducing users' utilities.

Difference in Total System Travel Time (TT)

This indicator has been largely adopted to evaluate network performance variations (Jenelius et al. 2006; Rupi et al. 2015b; Scott et al. 2006):

$$TT^{(e)} = \sum_i \sum_{j \neq i} x_{ij}^{(e)} t_{ij}^{(e)} - \sum_i \sum_{j \neq i} x_{ij}^{(0)} t_{ij}^{(0)} \qquad (4)$$

where the indices e and *0* refer to degraded (with the removal of link e) and current network, respectively; x_{ij} is the travel demand from traffic zone i to zone j and t_{ij} is the corresponding minimum travel time, which includes intersection delays, and it was calculated in the *Network Traffic Assignment* sub-model through a Deterministic User Equilibrium model.

Link Importance Index (LI)

According to Jenelius, Petersen and Mattsson (2006) links which cause isolation of some centroids, if removed, are called cut-links and generate unsatisfied demand. Link Importance Index was proposed by Rupi et al. (2015a, 2015b) to quantify the importance of link e for cut-links and non-cut-links. It is defined as:

$$LI_e = \beta F(ADT_e) + (1 - \beta) G(\Delta C_e) \qquad (5)$$

The index consists of two parts, whose relative weights are given by the parameter β, which ranges from 0 to 1 and is fixed by the analyst: $F(ADT_e)$ is the "local importance", which considers the link level of usage (measured by Average Daily Traffic, ADT), and $G(\Delta C_e)$ is the "global importance", which considers the effects of link closure in the network.

In this paper, the former ($F(ADT_e)$) has been calculated as:

$$F(ADT_e) = \frac{DT_e - DT_{min}}{DT_{max} - DT_{min}} \tag{6}$$

where DT_{max} and DT_{min} are respectively the maximum and minimum daily traffic (*DT*) among all the links of the current network, as estimated by the model.

The latter ($G(\Delta C_e)$) has been calculated as:

$$G(\Delta C_e) = \frac{g_e - g_{min}}{g_{max} - g_{min}} \tag{7}$$

where g_{max} and g_{min} are respectively the maximum and minimum values among the links in the network, and g_e is:

$$g_e = \Delta C_e + \alpha d_{ij}^e \tag{8}$$

where ΔC_e is the travel time total variation after the closure of link *e* (with respect to the current network configuration); d_{ij}^e is the corresponding unsatisfied demand from *i* to *j*; and parameter α is determined to obtain higher values of g_e after removing a cut-link than removing a non-cut-link.

Case study

The road transport network of the municipality of Dolo, in the province of Venice, northern Italy, was used to illustrate the vulnerability analysis under different scenarios using the proposed methodology and model. The results of the analysis were used by local authorities in the urban traffic planning process, to define proper maintenance investments and management strategies, basing their decision on realistic and reliable results.

The total population of Dolo is 14982 with 624 per km^2 density (ISTAT 2011). The road network model consists of 83 traffic zones (65 internal and 18 external zones), 2389 one-way links and 1121 nodes, including connectors and different road types as shown in Figure 2. The model also includes 523 intersections, represented by Cube Voyager sub-model, which provides representation of intersection geometry and signal phasing (signalized and un-signalized intersections, roundabouts), and calculates delays suffered by network users. BPR-type travel time functions were adopted for simulations, according to road types.

The vulnerability analysis was conducted to a subset of 52 links (candidate links in Figure 2), to reduce the computational burden due to ABM's runs (on a Dual Core Intel Pentium D Processor 3.2 GHz with a 2 GB RAM, the ABM took about 15 minutes per scenario) and to ease the comparison of results. In particular, links were selected according to the following criteria:

1. After an analysis of flow in the current network, road links with the largest traffic flows were identified. These links belong to main corridors, whose closures would have major effects on the network;
2. The most congested nodes were observed and arcs belonging to the most important intersections were selected;
3. Links in Dolo downtown area was considered, since few detours exist in case of their closure;
4. The most vulnerable links from a structural perspective, such as bridges, were selected.

The list of candidate links thus obtained was proposed and approved by technicians of Dolo local authority.

The link closure was simulated by excluding the link from the routes calculation in the assignment phase; in few cases the simulation produced cut-link conditions, that is the isolation of some centroids and unsatisfied demand. This result appears unrealistic, but this is due to the case-study network model configuration, since in practice users may take detours outside the study area. These simplifications did not affect the overall validity of the analysis and gave the chance to analyse the cut-links cases, which can occur in other contexts. The ABM model can be applied to larger networks, adjusting model parameters with proper calculators in order to reduce the computational burden; e.g. Miller et al. (2015) tested an ABM on a real network with more than 32000 links and 11900 nodes.

Although other modes might be introduced and modelled in the ABM, such as public transport and bike, in this phase they were not considered since the primary aim is to test the application of the proposed model in the vulnerability analysis. This means estimating inconveniences of users that, using car in the current scenario, are not able to perform their trip any more or they are compelled to change route, destination or period of their trips and activities, due to degradation of network performances after link closure. Since negative impacts evaluated though the ABM are defined as the users' inability to perform trips and activities as they scheduled with the travel mode chosen (car) in the current scenario, only car mode was considered.

Model Implementation

To obtain a realistic representation of daily activity, the ABM was implemented with some assumptions, discussed in the following paragraphs.

Data collection and socio-economic characteristics

The ABM needs detailed input data, which were collected at different level of aggregation by Italian agencies (e.g. municipalities, Italian National Statistics Institute):

- For each traffic zone:
    - Number of households living in the zone;
    - Number of students (high- and middle-school enrolment);
    - Number of employees, grouped in three sectors: service, retail, other.
- For each household:
    - Total household income (four income classes);
    - Number of household members.
- For a sample (5.3 %) of households, household members personal data (from a specific households survey):
    - Age;
    - Employment status.

Mandatory activities

Mandatory activities (i.e. work, school) estimated by the ABM in the base scenario (current network) were constrained to be preserved in the degraded conditions; this means that persons do not change their destination after link removal. Other types of activities may be done in other zones or not be carried out any more.

Relationships with external traffic zones

Unlike previous studies, (Bowman et al. 2006; Shan et al. 2013; Zhang et al. 2013) the ABM applied in this work includes the modelling of internal-external trips, which in many cases may represent a relevant portion of travel demand in a study area. It was assumed that opportunities outside the study-area (e.g. jobs, service areas) can represent feasible alternatives to current choices for persons living in the area and therefore must be represented in the model. The following procedure was implemented to model this aspect:

(1) From households survey data, internal-internal and internal-external trips were selected and categorized according to their purpose (work, school, retail, service, other);
(2) For internal-external trips selected in step 1, each trip destination (outside the study area) was recoded to match the corresponding external TAZ;
(3) For each purpose and for each internal TAZ, the rate between the number of opportunities (e.g. employees, students) and the number of internal-internal trips was determined;
(4) The total amount of opportunities in the external TAZs (employees, students) "available for internal users" was estimated multiplying the rates obtained in step 3 by the number of internal-external trips;
(5) The total amount of opportunities was assigned to each external TAZ proportionally to the number of internal-external trips obtained through steps 1 and 2.

Other types of trips (external-internal and external-external) were assumed as exogenous input data, taking values from pre-existing matrices (for the same study-area), generated by household and intercept (external cordon) surveys, properly adjusted with traffic count data. Since the aim of this paper is to evaluate inconveniences of people living in the study area, only internal-internal and internal-external trips were simulated through the ABM; however, since external-internal and external-external trips were not negligible, and, in order to obtain realistic results in terms of network performances, this type of demand was added to the corresponding matrices at each iteration of the ABM.

Model Calibration and Validation

One of main interests of this paper was proving the capabilities of the ABM in vulnerability analysis, inspecting the effects of users' activities and accessibility changes due to link disruption (i.e. in relative terms). The model adopted for the analysis was based on parameter values obtained in other contexts (Bowman et al. 2006) and partially modified to better represent Italian application conditions. Specific and more detailed model calibration for the Italian context will be developed in a second phase of the present work.

The validation process was conducted, as done by other authors (Bowman et al. 2006; Siripirote et al. 2015; Vuk et al. 2015; Zhang et al. 2013), comparing the demand estimated with the ABM (base scenario) and the current demand observed for the same study-area. The comparison was satisfactory, since the population living in the study area estimated by the model is 1.1% lower than the current one on base year; furthermore the estimated trips with internal origin and destination was 3% lower than the trips observed in the study area for the AM-Peak period, and 15% higher for the PM-Peak period; in addition the trip distribution in time periods is similar to the current case.

Results and discussion

The analysis of results considered mean indicator values for each scenario in a full workday period (24 hours) for car travel mode. For sake of brevity, results are reported only for worst scenarios.

Results with Activity-Based Model

Table 1 reports Mean Accessibility per Person (MAP), System Total Travel Time (TT), Average travel time per person (ATTP) and Link Importance Index (LI_e) for some values of β, obtained for worst candidate links disruption.

Observing Table 1 one can note that link closure affects link performance depending on link type (cut-link or non-cut-link); moreover, observing each indicator, different effects can be shown. The most vulnerable links seem to be link 100409 for non-cut-links and link 110106 for cut-links. Both links belong to main corridors: link 100409 is a bridge on the north-south urban corridor, and link 110106 is a rural link in the main east-west corridor. Moreover when removing a non-cut-link, TT and ATTP increase and MAP decreases, since the network changes reduce global accessibility and users are forced to make long detour; on the contrary when removing a cut-link, TT and MAP decrease, since accessibility decreases and travel demand loaded onto the system is reduced by network disruption (before the assignment).

The results for indicator LI_e depend on the value of parameter β adopted, that is the relative weight given to local and global importance. A sensitivity analysis was performed, increasing the parameter β from 0 to 1. It was found that for values of β equal to 0.25 and 0.50, link 110106 (cut-link) is the most vulnerable; for β equal to 0.75 it is link 100409 (non-cut-link). In conclusion link rankings are similar, but not identical, since indicators are based on different factors, such as network performance and users' characteristics.

To better compare rankings of 52 candidate links, Spearman's rank correlation coefficient ρ was calculated. Results show that TT-MAP correlation is quite high (ρ=0.68), and that TT-LI_e and MAP-LI_e correlations increase as the value of parameter β increases, even if they are lower than TT-MAP correlation (for β=0.75, TT-LI_e ρ=0.58 and MAP-LI_e ρ=0.66). This confirms that rankings change when considering different importance indexes.

To understand the complex effects due to travel demand changes, variations in tours characteristics were further analyzed;

Table 2 reports percentage differences between damaged and base scenarios. The results suggest that link closure produces changes in users' activities (trip chains), since average trips per person and average trips per tour vary in degraded networks. Furthermore, when removing a non-cut-link, average distance and average time per tour increase, since users are forced to make long detour. Number of tours and trips (total and per person) may vary for each scenario; on the contrary when removing a cut-link, average distance, average time, the number of tours and trips decrease. These reductions are due to less persons travelling in the network as a consequence of unsatisfied demand.

The results were consistent to ABM framework. Link closure produces network performance decay, that users perceive as a reduction of utilities associated with activities conducted in some zones of the study area. As the utilities decrease in these zones, zonal accessibility decreases and affects the scheduling of daily activities. The analysis of O/D matrices shows that spatial and temporal tour configuration changes in degraded networks: users choose new destinations and modify their trip chains, with tours longer than current ones.

In particular, high vulnerability of link 100409 is consistent with study area characteristics, since this link is one of three bridges crossing the river in the area and its closure forces users to long detours.

Comparison with Fixed Demand Model

The same vulnerability indicators were calculated with a Fixed Demand Model (FDM) and reported in Table 3 for worst candidate links.

According to the results, one can observe some differences between FDM and ABM. First TT increases for non-cut-links, because original demand is assigned to a degraded network, and decreases for cut-links, because of travel demand unassigned to the network. Absolute values are greater than those obtained with ABM, since the demand did not change in the degraded networks. Second MAP does not vary in the degraded network, since travel demand is assumed fixed; and LI_e absolute values are generally lower than those obtained with ABM.

As obtained with ABM, the most vulnerable links are link 100409 for non-cut-links and link 110106 for cut-links, but the link ranking changes, as confirmed by the analysis of Spearman's rank correlation coefficient ρ for candidate links. Analysis shows that correlation between FDM and ABM is very high (ρ=0.98) for TT, but low for LI_e, ranging from ρ=0.20 (β=0.25), to ρ=0.48 (β=0.75).

Results obtained with ABM seems to be more reliable those obtained with FDM, which did not take into account spatial distribution of activities and trips, due to unrealistic assumptions of unchanged travel demand after network degradation.

Spatial Analysis of Accessibility

For the two worst scenarios previously identified, the analysis was extended considering the impact of link disruption on accessibility, which has a significant role in the ABM. Figure 3 shows the variation in Mean Accessibility perceived by persons living in each TAZ due to link closure. In particular, people living in TAZ with dark colors experience lower utilities in carrying out activities in other TAZ, respect to the current scenario; therefore, their perceived accessibilities towards other TAZ are very low. Observing this figure, one can note that for the worst non cut-link (100409, left), MAP always decreases, in particular for persons living in southern TAZs, who usually use the link to move towards northern TAZs. Similarly for the worst cut-link (110106, right), MAP strongly decreases for TAZ 12, which is isolated after link removal. For persons living in TAZ 77, there is a slight increase in MAP, due to network performance improvements after travel demand reduction.

Again, since ABM simulates spatial and temporal variations in users' daily activities, modifying users' travel utilities, results obtained with this model are more reliable than those obtained with FDM, which does not take into account accessibility and tour changes after network degradation. This fact represents a strong limitation to apply FDM in the evaluation of socio-economic effects in vulnerability analysis.

Conclusions

In this paper road network vulnerability was evaluated by the analysis of link degradation effects on accessibility and network performance, considering travel demand changes. An Activity-Based Model was used to overcome unrealistic assumptions of fixed travel demand; relationships with external traffic zones, and spatiotemporal constraints connected with mandatory activities were considered and modelled properly. Link importance was evaluated with a set of vulnerability indicators, and specific analysis was carried out to underline effects of accessibility changes on travel demand.

The proposed methodology was applied to a real road network, simulating link closure effects independently of the type of event which causes it, building an approach that can be adopted for any disruptive event. The results of the analysis were significant for local authorities to define proper management strategies in the urban traffic plan.

Results produced by Activity-Based Model are consistent and significant. The model takes into account spatial distribution of activities and trips, due to changes in accessibility perceived by users.

In particular, results obtained with Activity-Based Model are more reliable than those obtained with Fixed Demand Model, which has unrealistic assumptions of unchanged travel demand after network degradation. Therefore, this methodology can be adopted to generate strong and consistent bases, useful for decision makers to allocate limited resources in prioritizing interventions on vulnerable links.

In the specific case study, the most vulnerable links are the same applying both models, but link ranking is not the same. For investments and management strategies this fact is relevant and must be considered by authorities, since the best allocation of resources may change depending on link ranking.

According to the above results, this study could be extended in various ways: extension of Activity-Based Model calibration to better represent users' behavior in Italy, complete validation of the model, by the comparison with the effects observed in case of link closure in real road networks, and a deeper analysis of Activity-Based Model results, including temporal distribution of activities, modal split modifications, equity effects of accessibility changes. Furthermore, the Activity-Based Model might be applied to a larger network, by modifying model parameters; the associated computational burden might be reduced by adopting proper calculators and/or focusing on a subset of links identified through automated selection criteria. Further detailed data are required to extend the network including external zones and, therefore, modelling trips originated in these zones. Moreover, the research can be extended considering other travel modes beyond car, in order to evaluate the modal shift caused by network degradation and, in particular, to test how the Activity-Based Model can simulate how users might decrease their inconveniences by changing their mode. An authors' research is currently evaluating model transferability to other study areas with proper data for the calibration phase.

To sum up, respect to Fixed Demand Model, the Activity-Based Model produces reliable and significant results which contribute to create sound bases to transportation planners and local authorities. On the other hand, it requires higher computational time and a lot of detailed data to be calibrated due to its complexity. However, once created, its model structure can be adopted and modified to identify critical infrastructure and proper policy interventions to prevent traffic congestions and other disadvantages.

Acknowledgements

The authors thank the Municipality of Dolo for the data used in this study.

References

Balijepalli, C., and Oppong, O. (2014). “Measuring vulnerability of road network considering the extent of serviceability of critical road links in urban areas.” *Journal of Transport Geography*, Elsevier Ltd, 39, 145–155.

Berdica, K. (2002). “An introduction to road vulnerability : what has been done , is done and should be done.” *Transport Policy*, 9, 117–127.

Bono, F., and Gutiérrez, E. (2011). “A network-based analysis of the impact of structural damage on urban accessibility following a disaster: the case of the seismically damaged Port Au Prince and Carrefour urban road networks.” *Journal of Transport Geography*, Elsevier Ltd, 19(6), 1443–1455.

Bowman, J. L., and Bradley, M. A. (2005). “Disaggregate Treatment of Purpose, Time of Day and Location in an Activity-Based Regional Travel Forecasting Model.” *European Transport Conference*, Strasbourg, France.

Bowman, J. L., Bradley, M. A., Gibb, J., and DKS Associates. (2006). “The Sacramento Activity-Based Travel Demand Model: Estimation And Validation Results.” *European Transport Conference*, Strasbourg, France, 1–31.

Cai, H., Zhu, J., Yang, C., Fan, W., and Xu, T. (2017). “Vulnerability Analysis of Metro Network Incorporating Flow Impact and Capacity Constraint after a Disaster.” *Journal of Urban Planning and Development*, 143(2).

Carturan, F., Pellegrino, C., Rossi, R., Gastaldi, M., and Modena, C. (2013). “An integrated procedure for management of bridge networks in seismic areas.” *Bulletin of Earthquake Engineering*, 11, 543–559.

Cascetta, E., Cartenì, A., and Montanino, M. (2013). “A New Measure of Accessibility based on Perceived Opportunities.” *Procedia - Social and Behavioral Sciences*, Elsevier B.V., 87, 117–132.

Caschili, S., Romana Medda, F., and Reggiani, A. (2015). “Guest editorial: Resilience of Networks.” *Transportation Research Part A: Policy and Practice*, 81, 1–3.

Cats, O., Yap, M., and van Oort, N. (2016). “Exposing the role of exposure: Public transport network risk analysis.” *Transportation Research Part A: Policy and Practice*, Elsevier Ltd, 88, 1–14.

Chen, A., Yang, C., Kongsomsaksakul, S., and Lee, M. (2007). “Network-based Accessibility Measures for Vulnerability Analysis of Degradable Transportation Networks.” *Networks and Spatial Economics*, 7, 241–256.

Chen, Y. B., Lam, W. H. K., Sumalee, A., Li, Q., and Li, Z. (2012). “Vulnerability analysis for large-scale and congested road networks with demand uncertainty.” *Transportation Research Part A*, Elsevier Ltd, 46(3), 501–516.

D’Este, G. M., and Taylor, M. A. P. (2001). “Modelling network vulnerability at the level of the nationale strategic transport network.” *Journal of Eastern Asia Society for Transortation Studies*, 4(2), 1–14.

D’Este, G. M., and Taylor, M. A. P. (2003). “Network vulnerability: an approach to reliability analysis at the level of national strategic transport networks.” *The Network Reliability of Transport*, M. G. H. (Eds. . Iida, Y. Bell, ed., Elsevier, Oxford, 23–44.

Dalziell, E., and Nicholson, A. (2001). “Risk and impact of natural hazards on a road network.” *Journal of Transportation Engineering*, 127(April), 159–166.

Dehghani, M. S., Flintsch, G., and Mcneil, S. (2017). “Parametric Analysis of Roadway Infrastructure Vulnerability to Disruptions.” *Journal of Infrastructure Systems*, 23(4), 1–9.

Du, M., Jiang, X., and Cheng, L. (2017). “Alternative network robustness measure using system-wide transportation capacity for identifying critical links in road networks.” *Advances in Mechanical Engineering*, 9(4), 1–12.

El-rashidy, R. A., and Grant-muller, S. M. (2014). “An assessment method for highway network vulnerability.” *Journal of Transport Geography*, Elsevier Ltd, 34, 34–43.

Erath, A., Birdsall, J., Axhausen, K. W., and Hajdin, R. (2010). “Vulnerability Assessment Methodology for Swiss Road Network.” *Transportation Research Record: Journal of the Transportation Research Board*, 2137, 118–126.

Faturechi, R., and Miller-Hooks, E. (2014). “Measuring the performance of transportation infrastructure systems in disasters: A comprehensive review.” *ASCE Journal of Infrastructure Systems*, 21(1), 1–15.

Guo, A., Liu, Z., Li, S., and Li, H. (2017). “Seismic performance assessment of highway bridge networks considering post-disaster traffic demand of a transportation system in emergency conditions.” *Structure and Infrastructure Engineering*, Taylor & Francis, 13(12), 1523–1537.

Hu, T., and Ho, W. (2013). “Prediction of Typhoon Impact on Transportation Networks with Support Vector Regression.” *Journal of Transportation Engineering*, 141(4), 1–11.

Husdal, J. (2004). “Reliability and vulnerabbility versus costs and benefits.” *The Second International Symposium on Transportation Network Reliability (INSTR)*, Christchurch and Qeenstown, NZ.

ISTAT. (2011). “Popolazione Residente.” <http://datiopen.istat.it/datasetOntologie.php?call>.

Jenelius, E. (2007). “Incorporating Dynamics and Information in a Consequence Model for Road Network Vulnerability Analysis.” *The Third International Symposium on Transportation Network Reliability (INSTR)*, The Hague, The Netherlands.

Jenelius, E. (2009). “Network structure and travel patterns : explaining the geographical disparities of road network vulnerability.” *Journal of Transport Geography*, Elsevier Ltd, 17(3), 234–244.

Jenelius, E. (2010). “User inequity implications of road network vulnerability.” *Journal of Transport and Land Use*, 2, 57–73.

Jenelius, E., and Mattsson, L. (2012). “Road network vulnerability analysis of area-covering disruptions : A grid-based approach with case study.” *Transportation Research Part A*, Elsevier Ltd, 46(5), 746–760.

Jenelius, E., and Mattsson, L. (2015). “Computers , Environment and Urban Systems Road network vulnerability analysis : Conceptualization , implementation and application.” *Computers, Environment and Urban Systems*, Elsevier Ltd, 49, 136–147.

Jenelius, E., Petersen, T., and Mattsson, L. (2006). “Importance and exposure in road network vulnerability analysis.” *Transportation Research Part A*, 40, 537–560.

Kermanshah, A., and Derrible, S. (2016). “A geographical and multi-criteria vulnerability assessment of transportation networks against extreme earthquakes.” *Reliability Engineering & System Safety*, Elsevier, 153, 39–49.

Knoop, V. L., Snelder, M., Zuylen, H. J. Van, and Hoogendoorn, S. P. (2012). “Link-level vulnerability indicators for real-world networks.” *Transportation Research Part A*, Elsevier Ltd, 46(5), 843–854.

Kontou, E., Murray-Tuite, P., and Wernstedt, K. (2017). “Duration of commute travel changes in the aftermath of Hurricane Sandy using accelerated failure time modeling.” *Transportation Research Part A: Policy and Practice*, Elsevier Ltd, 100, 170–181.

Lu, Q.-C., Peng, Z.-R., and Zhang, J. (2015). “Identification and Prioritization of Critical Transportation Infrastructure: Case Study of Coastal Flooding.” *Journal of Transportation Engineering*, 141(3).

Luathep, P., Sumalee, A., Ho, H. W., and Fumitaka, K. (2011). “Large-scale road network vulnerability analysis: a sensitivity analysis based approach.” *Transportation*, 38, 799–817.

Miller, M., Cortes, S., Ory, D., and Baker, J. W. (2015). “Estimating probabilistic impacts of catastrophic network damage from earthquakes using an activity-based travel model.” *Transportation Research Board 94th Annual Meeting*, Washington DC, United States.

de Oliveira, E. L., Portugal, L. da S., and Porto Junior, W. (2016). “Indicators of reliability and vulnerability: Similarities and differences in ranking links of a complex road system.” *Transportation Research Part A: Policy and Practice*, Elsevier Ltd, 88, 195–208.

Ortuzar, D., and Willumsen, L. G. (2011). *MODELLING TRANSPORT 4th Edition*. (Wiley, ed.).

Papa, E., and Coppola, P. (2012). “Gravity-Based Accessibility Measures for Integrated Transport-Land Use Planning (GraBAM).” *Accessibility Instruments for Planning Practice*, 117–124.

Reggiani, A., Nijkamp, P., and Lanzi, D. (2015). "Transport resilience and vulnerability: The role of connectivity." *Transportation Research Part A: Policy and Practice*, Elsevier Ltd, 81, 4–15.

Rupi, F., Angelini, S., Bernardi, S., Danesi, A., and Rossi, G. (2015a). "Ranking links in a road transport network : a practical method for the calculation of link importance." *Transportation Research Procedia*, Elsevier B.V., 5, 221–232.

Rupi, F., Bernardi, S., Rossi, G., and Danesi, A. (2015b). "The Evaluation of Road Network Vulnerability in Mountainous Areas : A Case Study." *Networks and Spatial Economics*, 15(2), 397–411.

Sakakibara, H., Kajitani, Y., and Okada, N. (2004). "Road Network Robustness for Avoiding Functional Isolation in Disasters." *Journal of Transportation Engineering*, 130(October), 560–567.

Scott, D. M. (2006). "Embracing activity analysis in transport geography: Merits, challenges and research frontiers." *Journal of Transport Geography*, 14(5), 389–392.

Scott, D. M., Novak, D. C., Aultman-hall, L., and Guo, F. (2006). "Network Robustness Index : A new method for identifying critical links and evaluating the performance of transportation networks." *Journal of Transport Geography*, 14, 215–227.

Shan, R., Zhong, M., Du, D., and Lu, C. (2013). "Comparison of Trip Generation Results from Activity-based and Traditional Four-Step Travel Demand Modeling: A Case Study of Tampa, Florida." *ICTIS 2013*, Fredericton, New Brunswick, 627–633.

Siripirote, T., Sumalee, A., Ho, H. W., and Lam, W. H. K. (2015). "Statistical approach for activity-based model calibration based on plate scanning and traffic counts data."

Transportation Research Part B: Methodological, 78, 280–300.

Taylor, M. A. P. (2008). “Critical Transport Infrastructure in Urban Areas: Impacts of Traffic Incidents Assessed Using Accessibility-Based Network Vulnerability Analysis.” *Growth and Change*, 39(4), 593–616.

Taylor, M. A. P., Sekhar, S. V. C., and D’Este, G. M. (2006). “Application of Accessibility Based Methods for Vulnerability Analysis of Strategic Road Networks.” *Networks and Spatial Economics*, 6, 267–291.

Taylor, M. A. P., and Susilawati. (2012). “Remoteness and accessibility in the vulnerability analysis of regional road networks.” *Transportation Research Part A*, Elsevier Ltd, 46(5), 761–771.

Vuk, G., Bowman, J. L., Daly, A., and Hess, S. (2015). “Impact of household time constraints on person travel demand.” *Transportation*, 1–20.

Wang, D. Z. W., Liu, H., Szeto, W. Y., and Chow, A. H. F. (2016). “Identification of critical combination of vulnerable links in transportation networks – a global optimisation approach.” *Transportmetrica A: Transport Science*, 12(4), 346–365.

Wang, Z., Chan, A. P. C., Yuan, J., Xia, B., Skitmore, M., and Li, Q. (2015). “Recent Advances in Modeling the Vulnerability of Transportation Networks.” *Journal of Infrastructure Systems*, American Society of Civil Engineers, 21(2).

Zanini, M. A., Faleschini, F., Zampieri, P., Pellegrino, C., Gecchele, G., Gastaldi, M., and Rossi, R. (2017). “Post-quake urban road network functionality assessment for seismic emergency management in historical centres.” *Structure and Infrastructure Engineering*, Taylor & Francis, 13(9), 1117–1129.

Zhang, L., Yang, W., Wang, J., and Rao, Q. (2013). “Large-Scale Agent-Based Transport Simulation in Shanghai, China.” *Transportation Research Record: Journal of the Transportation Research Board*, 2399, 34–43.

Figure captions

Fig. 1. Simplified structure of the Activity-Based Model

Fig. 2. Case study area.

Fig. 3. Difference of MAP values from base scenario for links a) 100409 and b) 110106

Tables

Table 1. Activity-Based Model. Performance indicators for worst scenarios

Link Type	**Link Code**	**TT**	**ATTP**	**MAP**		**LI_e**	
		[%]	**[%]**	**[%]**	**β = 0.25**	**β = 0.50**	**β = 0.75**
NCL	100409	438.8	46.6	-19.066	0.448	0.599	0.750
NCL	200131	350.5	21.4	-9.703	0.396	0.556	0.716
NCL	100525	225.8	21.4	-9.780	0.258	0.363	0.468
NCL	100368	71.4	3.4	-1.171	0.099	0.151	0.202
NCL	100577	59.9	26.9	-9.195	0.180	0.320	0.460
NCL	200058	59.8	8.4	-4.491	0.260	0.479	0.698
NCL	100397	40.0	17.6	-10.420	0.201	0.375	0.549
NCL	103789	29.3	8.0	-4.295	0.172	0.324	0.476
NCL	102442	29.3	8.0	-4.295	0.172	0.324	0.476
NCL	108431	28.1	16.6	-9.619	0.211	0.403	0.594
CL	110105	-8.9	0.0	-0.972	0.439	0.348	0.257
CL	110106	-25.2	1.0	-9.251	0.915	0.831	0.746

Note: ATTP = average travel time per person; NCL = non-cut-link; CL= cut-link.

Table 2. Percent variations of tour characteristics from base scenario.

Link Type	**Link Code**	**Number of Tours**	**Tours per Person**	**Number of Trips**	**Trips per Person**	**Trips per Tour**	**Average Distance per Tour**	**Average Time per Tour**
NCL	100409	-0.005	-0.452	-0.001	-0.120	0.003	0.152	0.330
NCL	100577	-0.002	-0.190	-0.001	-0.103	0.001	0.029	0.161
NCL	200131	-0.002	-0.005	-0.004	-0.182	-0.002	0.037	0.159
NCL	100525	-0.006	-0.260	-0.008	-0.481	-0.002	0.034	0.153
NCL	108431	-0.001	0.087	0.001	0.323	0.002	0.153	0.145
NCL	200036	-0.003	-0.205	-0.003	-0.198	0.000	0.061	0.120
NCL	100397	-0.002	-0.139	-0.004	-0.282	-0.001	0.112	0.113
NCL	100599	-0.006	-0.095	-0.001	0.379	0.005	0.028	0.091
NCL	200058	-0.003	-0.084	-0.004	-0.165	-0.001	0.070	0.090
NCL	102442	-0.003	-0.202	-0.004	-0.304	-0.001	0.095	0.067
CL	100483	-0.089	-4.490	-0.090	-4.577	-0.001	-0.003	-0.002
CL	110106	-0.153	-4.558	-0.153	-4.570	0.000	-0.034	-0.025

Note: NCL = non-cut-link; CL = cut-link.

Table 3. Fixed Demand Model. Performance indicators for worst scenarios

Link Type	**Link Code**	**TT [%]**		**MAP [%]**		**LI_e**					
						β = 0.25		**β = 0.50**		**β = 0.75**	
		FDM	**ABM**	**FDM**	**ABM**	**FDM**	**ABM**	**FDM**	**ABM**	**FDM**	**ABM**
NCL	100409	502.2	438.8	-	-19.066	0.416	0.448	0.578	0.599	0.740	0.750
NCL	200131	388.8	350.5	-	-9.703	0.110	0.396	0.217	0.556	0.324	0.716
NCL	100525	278.4	225.8	-	-9.780	0.074	0.258	0.147	0.363	0.221	0.468
NCL	100577	74.4	59.9	-	-9.195	0.142	0.180	0.273	0.320	0.404	0.460
NCL	100368	74.4	71.4	-	-1.171	0.092	0.099	0.146	0.151	0.200	0.202
NCL	200058	63.5	59.8	-	-4.491	0.119	0.260	0.238	0.479	0.356	0.698
NCL	100397	40.2	40.0	-	-10.420	0.196	0.201	0.372	0.375	0.548	0.549
NCL	108431	29.7	28.1	-	-9.619	0.114	0.211	0.224	0.403	0.334	0.594
NCL	102442	29.5	29.3	-	-4.295	0.168	0.172	0.322	0.324	0.475	0.476
NCL	103789	29.4	29.3	-	-4.295	0.101	0.172	0.200	0.324	0.299	0.476
CL	100483	-7.9	-8.7	-	-0.972	0.030	0.494	0.061	0.401	0.091	0.308
CL	110106	-30.8	-25.2	-	-9.251	0.186	0.915	0.368	0.831	0.550	0.746

Note: AB = Activity-Based Model; FDM = Fixed Demand Model; NCL = non-cut-link; CL= cut-link;

- = (for MAP) indicator has no variation.