

Road Network Vulnerability Analysis: Case Study Considering Travel Demand and Accessibility Changes

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

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20 **Abstract**

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

32 depend on correct link vulnerability analysis and ranking.

33 **Introduction**

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

44 According to several authors (Faturechi and Miller-Hooks 2014; de Oliveira et al.
45 2016; Reggiani et al. 2015), the vulnerability concept still lacks a consensus definition, and it
46 depends on the application context (Caschili et al. 2015; El-rashidy and Grant-muller 2014).
47 The first formalization of the concept in transport analysis can be found in Berdica (2002),
48 who defines “vulnerability” as “a susceptibility to incidents that can result in considerable
49 reductions in road network serviceability”, where serviceability of a link/route/road network
50 is interpreted as “the possibility to use that link/route/road network during a given period”.
51 Other concepts related to vulnerability are robustness and reliability (D’Este and Taylor 2003;
52 Faturechi and Miller-Hooks 2014; de Oliveira et al. 2016; Reggiani et al. 2015; Rupi et al.
53 2015b): robustness focuses on the impacts of the disturbance (e.g. decrease of network
54 performance), reliability focuses on the frequency of occurrence of the disturbance, that is on
55 its probability. For other authors (Bono and Gutiérrez 2011; Husdal 2004; Luathep et al.

56 2011), reliability is a measure of network stability, and vulnerability should be a measure of
57 the consequences of a network element collapse (or underfunctioning) (Cai et al. 2017;
58 Faturechi and Miller-Hooks 2014).

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

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

65 Following past studies approach (Jenelius, 2009; 2010, Jenelius and Mattsson, 2015;
66 Rupi et al., 2015b), the “importance” was used to measure the impacts of link disruption. In
67 practice, link importance is commonly estimated with vulnerability indicators, which compare
68 network performance before (current network) and after (“degraded” network) the link
69 closure. The most common indicators are based on total system cost (often, the travel time)
70 (Balijepalli and Oppong 2014; Carturan et al. 2013; Dalziell and Nicholson 2001; Dehghani et
71 al. 2017; Guo et al. 2017; Hu and Ho 2013; Jenelius et al. 2006; Jenelius 2007, 2009, 2010,
72 Jenelius and Mattsson 2012, 2015; de Oliveira et al. 2016; Rupi et al. 2015a, 2015b; Scott
73 2006; Taylor et al. 2006; Wang et al. 2016); others refer to accessibility measures (D’Este and
74 Taylor 2001; Kermanshah and Derrible 2016; Lu et al. 2015; Miller et al. 2015; Taylor 2008;
75 Taylor et al. 2006; Taylor and Susilawati 2012), connectivity (Scott et al. 2006; Zanini et al.
76 2017), topological measure of dispersiveness/concentration (Sakakibara et al. 2004), distance
77 travelled, link flow and capacity (Balijepalli and Oppong 2014; Chen et al. 2012; Guo et al.
78 2017).

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

85 In both cases, the literature review highlighted that the majority of authors adopted the
86 inelastic (or fixed) demand assumption for traffic simulation (Balijepalli and Oppong 2014;
87 Dehghani et al. 2017; Erath et al. 2010; Hu and Ho 2013; Jenelius et al. 2006; Jenelius 2007,
88 2009, 2010, Jenelius and Mattsson 2012, 2015; Kermanshah and Derrible 2016; Lu et al.
89 2015; Luathep et al. 2011; de Oliveira et al. 2016; Wang et al. 2016). This means that travel
90 demand is independent of changes in network level of service and traffic models may
91 represent route choice changes (detour), but changes in trip mode, destination or time period
92 may not be considered.

93 Since disruptive events cause variations in travel demand (Kontou et al. 2017), this
94 paper adopted an Activity-Based Model, which allows simulating users' responses to changes
95 in network configuration, modifying travel demand according to spatial accessibility
96 variations. These aspects have been considered in few studies (Chen et al. 2007, 2012;
97 Dalziell and Nicholson 2001; El-rashidy and Grant-muller 2014; Guo et al. 2017; Miller et al.
98 2015; Taylor 2008) but still need to be developed and further analysed. Investigating the
99 effects of Desert Road closure in New Zeland, Dalziell and Nicholson (2001) considered
100 travel demand elasticity and assumed that some trips might not be performed if the increase of
101 travel cost due to link closure exceed a certain value. In order to evaluate travel demand

102 changes in detail, Taylor (2008) and Miller et al. (2015) used an Activity-Based Model, and
103 Chen et al. (2007) and Du, Xiaowei and Cheng (2017) adopted a Combined Travel Demand
104 Model. However, in these papers models were limited to a single link or few links analysis
105 (Chen et al. 2007; Taylor 2008) or they were related to specific scenarios (such as earthquake
106 damage scenarios (Miller et al. 2015)).

107 As stated by Reggiani, Nijkamp and Lanzi (2015), “transport is a largely derived
108 demand, so that accessibility analyses, by including socio-economic elements, seem to be
109 crucial for the study of the resilience/vulnerability impacts from transport networks to socio-
110 economic-environmental networks”. Therefore, network degradation significantly affects
111 users’ accessibility (D’Este and Taylor 2001). Unlike the classical definition of accessibility,
112 which consider only characteristics on the supply side of a transportation system, Taylor
113 (2008) adopted a combined measure which considers also the demand side and travel
114 behavior of users. Fixed Demand Model is not suitable for such definition of accessibility,
115 therefore Activity-Based Model was adopted by several authors (Miller et al. 2015; Taylor
116 2008).

117 According to this perspective, this paper extended previous studies investigating the
118 roles of accessibility and travel demand changes in urban road network vulnerability, which
119 have received limited attention in the past. In order to evaluate these variations this paper
120 adopts an Activity-Based Model. The link importance is evaluated with a set of vulnerability
121 indicators adopting a vulnerability scan approach. In order to define a general methodology,
122 which can be largely adopted in any vulnerability analysis, no assumptions about the type and
123 the probability of occurrence of the event which produces the link closure are considered. The
124 Activity-Based Model evaluates accessibility and travel demand changes, and network

125 performance produced by link closure, providing realistic and, therefore, solid and reliable
126 results, which are useful to identify critical links. Moreover, by testing the proposed
127 methodology on a real urban network in Italy, this paper contributes to perform vulnerability
128 analysis for European case studies, which are very limited in previous works.

129 **Material and methods**

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

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

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

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

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

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

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

150 *Activity-Based Model*

151 In transport systems, supply changes may induce travel demand variations; in order to
152 simulate these effects, the vulnerability analysis has been conducted with an Activity-Based
153 Model (ABM). This model focuses on individual choices, assuming travel demand as derived
154 from the need to participate in activities (Scott 2006) and elastic (Ortuzar and Willumsen
155 2011), i.e. responsive to transport system changes (accessibility, in particular). The model
156 framework is based upon the work of Bowman and Bradley (2005), who developed and
157 applied an econometric activity-based microsimulation model for the Sacramento (California)
158 Area Council of Governments. In particular the disaggregated model simulates full-day
159 activity and travel schedule for each resident in the study area (Bowman and Bradley 2005).
160 The implemented ABM can be subdivided in the following sub-models (Figure 1).

161 (1) The *Population Synthesizer* generates the population in the study area from detailed
162 attributes of a sample of households and zonal characteristics (e.g. number of persons
163 living in a traffic zone). This sub-model expands disaggregate sample data (such as
164 gender, income, size) in order to match aggregate households' characteristics with an
165 Iterative Proportional Fitting process (Bowman et al. 2006; Bowman and Bradley
166 2005; Ortuzar and Willumsen 2011).

167 (2) The *Activity and Travel Simulator* simulates long term households' choices (e.g. work
168 and school location, number of cars owned) and personal daily activities, that is a
169 sequence of tours and trips carried out by each person belonging to the synthesized
170 population. Choices are simulated with a Nested Logit framework (Bowman et al.
171 2006; Bowman and Bradley 2005), according to population and accessibility
172 characteristics (zonal characteristics and transport network levels of service). In

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

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

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

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

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

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

- 200 • 3 travel modes (Single Occupancy Vehicles, High Occupancy Vehicles, Walk)
- 201 • 4 time periods (AM-peak period, MD period, PM-Peak period, Off-Peak period)
- 202 • 6 trip purposes (Work, School, Work-Based, Intermediate Stop, At Home, Other).

203 *Vulnerability and Accessibility indicators*

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

210 *Difference in Mean Accessibility per Person (MAP)*

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

$$216 \quad MAP^{(e)} = \frac{\frac{\sum_{s^{(e)}} A_s^{(e)}}{s^{(e)}} - \frac{\sum_{s^{(0)}} A_s^{(0)}}{s^{(0)}}}{\frac{\sum_{s^{(0)}} A_s^{(0)}}{s^{(0)}}}}{\frac{\sum_{s^{(0)}} A_s^{(0)}}{s^{(0)}}}} \quad (1)$$

217 where

$$218 \quad A_s = \ln \sum_{d=1}^D e^{V_{s,d}} \quad (2)$$

219 $s^{(0)}$ and $s^{(e)}$ are the flows of persons in the time period considered in the analysis who make
 220 a trip in current and degraded network, respectively; d is the set of destinations that person s
 221 can reach from his/her own home; $V_{s,d}$ is the systematic utility, the mean or expected value of
 222 utility perceived by persons having a choice set D , which depends on individual, zonal, and
 223 network parameters derived from the *Network Traffic Assignment* sub-model through a
 224 Deterministic User Equilibrium model. In this paper, these parameters were: number of
 225 employees in each sector and TAZ, presence of toll parking, minimum distance and travel
 226 time to reach a destination, number and age of household members, total household income
 227 and owned cars, tour purpose and time period of day. Coefficients of utility functions differ
 228 according to 3 travel modes, 4 time periods of the trip, 6 trips purpose, 4 household income
 229 classes and number of household cars (greater or less than 0); therefore the number of utility
 230 functions adopted is 576. For example, for car travel mode, AM – Peak period, work trip
 231 purpose, household income less than 33400 \$ and more than 0 household cars, the utility is
 232 calculated as (Bowman and Bradley 2005):

$$233 \quad V_{s,d} = -0.03t_{o,d} - 0.25d_{o,d} - 0.25toll_d \quad (3)$$

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

237 *Difference in Total System Travel Time (TT)*

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

$$240 \quad TT^{(e)} = \sum_i \sum_{j \neq i} x_{ij}^{(e)} t_{ij}^{(e)} - \sum_i \sum_{j \neq i} x_{ij}^{(0)} t_{ij}^{(0)} \quad (4)$$

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

245 *Link Importance Index (LI)*

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

$$250 \quad LI_e = \beta F(ADT_e) + (1 - \beta) G(\Delta C_e) \quad (5)$$

251 The index consists of two parts, whose relative weights are given by the parameter β ,
 252 which ranges from 0 to 1 and is fixed by the analyst: $F(ADT_e)$ is the "local importance",

253 which considers the link level of usage (measured by Average Daily Traffic, ADT), and
 254 $G(\Delta C_e)$ is the “global importance”, which considers the effects of link closure in the network.

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

$$256 \quad F(ADT_e) = \frac{DT_e - DT_{min}}{DT_{max} - DT_{min}} \quad (6)$$

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

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

$$260 \quad G(\Delta C_e) = \frac{g_e - g_{min}}{g_{max} - g_{min}} \quad (7)$$

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

$$263 \quad g_e = \Delta C_e + \alpha d_{ij}^e \quad (8)$$

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

268 **Case study**

269 The road transport network of the municipality of Dolo, in the province of Venice,
 270 northern Italy, was used to illustrate the vulnerability analysis under different scenarios using
 271 the proposed methodology and model. The results of the analysis were used by local

272 authorities in the urban traffic planning process, to define proper maintenance investments
273 and management strategies, basing their decision on realistic and reliable results.

274 The total population of Dolo is 14982 with 624 per km² density (ISTAT 2011). The
275 road network model consists of 83 traffic zones (65 internal and 18 external zones), 2389 one-
276 way links and 1121 nodes, including connectors and different road types as shown in Figure
277 2. The model also includes 523 intersections, represented by Cube Voyager sub-model, which
278 provides representation of intersection geometry and signal phasing (signalized and un-
279 signalized intersections, roundabouts), and calculates delays suffered by network users. BPR-
280 type travel time functions were adopted for simulations, according to road types.

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

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

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

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

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

315 ***Model Implementation***

316 To obtain a realistic representation of daily activity, the ABM was implemented with

317 some assumptions, discussed in the following paragraphs.

318 *Data collection and socio-economic characteristics*

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

- 321 • For each traffic zone:
 - 322 ○ Number of households living in the zone;
 - 323 ○ Number of students (high- and middle-school enrolment);
 - 324 ○ Number of employees, grouped in three sectors: service, retail, other.
- 325 • For each household:
 - 326 ○ Total household income (four income classes);
 - 327 ○ Number of household members.
- 328 • For a sample (5.3 %) of households, household members personal data (from a
329 specific households survey):
 - 330 ○ Age;
 - 331 ○ Employment status.

332 *Mandatory activities*

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

337 *Relationships with external traffic zones*

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

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

357 Other types of trips (external-internal and external-external) were assumed as
358 exogenous input data, taking values from pre-existing matrices (for the same study-area),

359 generated by household and intercept (external cordon) surveys, properly adjusted with traffic
360 count data. Since the aim of this paper is to evaluate inconveniences of people living in the
361 study area, only internal-internal and internal-external trips were simulated through the ABM;
362 however, since external-internal and external-external trips were not negligible, and, in order
363 to obtain realistic results in terms of network performances, this type of demand was added to
364 the corresponding matrices at each iteration of the ABM.

365 *Model Calibration and Validation*

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

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

380 **Results and discussion**

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

384 *Results with Activity-Based Model*

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

388 Observing Table 1 one can note that link closure affects link performance depending
389 on link type (cut-link or non-cut-link); moreover, observing each indicator, different effects
390 can be shown. The most vulnerable links seem to be link 100409 for non-cut-links and link
391 110106 for cut-links. Both links belong to main corridors: link 100409 is a bridge on the
392 north-south urban corridor, and link 110106 is a rural link in the main east-west corridor.
393 Moreover when removing a non-cut-link, TT and ATTP increase and MAP decreases, since
394 the network changes reduce global accessibility and users are forced to make long detour; on
395 the contrary when removing a cut-link, TT and MAP decrease, since accessibility decreases
396 and travel demand loaded onto the system is reduced by network disruption (before the
397 assignment).

398 The results for indicator LI_e depend on the value of parameter β adopted, that is the
399 relative weight given to local and global importance. A sensitivity analysis was performed,
400 increasing the parameter β from 0 to 1. It was found that for values of β equal to 0.25 and
401 0.50, link 110106 (cut-link) is the most vulnerable; for β equal to 0.75 it is link 100409 (non-

402 cut-link). In conclusion link rankings are similar, but not identical, since indicators are based
403 on different factors, such as network performance and users' characteristics.

404 To better compare rankings of 52 candidate links, Spearman's rank correlation
405 coefficient ρ was calculated. Results show that TT-MAP correlation is quite high ($\rho=0.68$),
406 and that TT-LI_e and MAP-LI_e correlations increase as the value of parameter β increases,
407 even if they are lower than TT-MAP correlation (for $\beta=0.75$, TT-LI_e $\rho=0.58$ and MAP-LI_e
408 $\rho=0.66$). This confirms that rankings change when considering different importance indexes.

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

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

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

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

429 ***Comparison with Fixed Demand Model***

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

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

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

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

447 *Spatial Analysis of Accessibility*

448 For the two worst scenarios previously identified, the analysis was extended
449 considering the impact of link disruption on accessibility, which has a significant role in the
450 ABM. Figure 3 shows the variation in Mean Accessibility perceived by persons living in each
451 TAZ due to link closure. In particular, people living in TAZ with dark colors experience
452 lower utilities in carrying out activities in other TAZ, respect to the current scenario;
453 therefore, their perceived accessibilities towards other TAZ are very low. Observing this

454 figure, one can note that for the worst non cut-link (100409, left), MAP always decreases, in
455 particular for persons living in southern TAZs, who usually use the link to move towards
456 northern TAZs. Similarly for the worst cut-link (110106, right), MAP strongly decreases for
457 TAZ 12, which is isolated after link removal. For persons living in TAZ 77, there is a slight
458 increase in MAP, due to network performance improvements after travel demand reduction.

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

464 **Conclusions**

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

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

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

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

484 In the specific case study, the most vulnerable links are the same applying both
485 models, but link ranking is not the same. For investments and management strategies this fact

486 is relevant and must be considered by authorities, since the best allocation of resources may
487 change depending on link ranking.

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

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

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- 668

669 **Figure captions**

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

671 **Fig. 2.** Case study area.

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

673 **Tables**674 **Table 1.** Activity-Based Model. Performance indicators for worst scenarios

Link Type	Link Code	TT	ATTP	MAP	LI _e		
		[%]	[%]	[%]	$\beta = 0.25$	$\beta = 0.50$	$\beta = 0.75$
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.

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

Link	Link	Number	Tours	Number	Trips	Trips	Average Distance	Average Time
Type	Code	of Tours	per Person	of Trips	per Person	per Tour	per Tour	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.

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

Link Type	Link Code	TT [%]	MAP [%]		LI _e							
			FDM	ABM	$\beta = 0.25$		$\beta = 0.50$		$\beta = 0.75$			
			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.