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Integrated platform to assess seismic resilience at the community level

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8 **Integrated platform to assess seismic resilience at** 9 **the community level**

10
11 **Abstract:** Due to the increasing frequency of disastrous events, the challenge of creating large-
12 scale simulation models has become of major significance. Indeed, several simulation
13 strategies and methodologies have been recently developed to explore the response of
14 communities to natural disasters. Such models can support decision-makers during emergency
15 operations allowing to create a global view of the emergency identifying consequences. An
16 integrated platform that implements a community hybrid model with real-time simulation
17 capabilities is presented in this paper. The platform's goal is to assess seismic resilience and
18 vulnerability of critical infrastructures (e.g., built environment, power grid, socio-technical
19 network) at the urban level, taking into account their interdependencies.

20 Finally, different seismic scenarios have been applied to a large-scale virtual city model. The
21 platform proved to be effective to analyze the emergency and could be used to implement
22 countermeasures that improve community response and overall resilience.

23 *Keywords: disaster resilience, urban community, interdependence analysis, critical*
24 *infrastructure, damage assessment, multiprocessing.*

25

26

LIST OF ABBREVIATION

27 **RTN:** Road Transportation Network

28 **WDN:** Water Distribution Network

29 **PG:** Power Grid

30 **STN:** Socio-Technical Network

31 **RV:** Random Variable

32 **MCS:** Monte Carlo Simulation

33 **RC:** Reinforced Concrete

34 **CPU:** Central Processing Unit

35 **GPU:** Graphical Processing Unit

36 **RF:** Random Forest

37 **KNR:** k-Nearest Neighbors

38 **DDM:** Density Design Method

39 **ABM:** Agent Based Model

40 **DS:** Damage State

41 **SC:** Single-Core

42 **MC:** Multi-Core

43

1. INTRODUCTION

44 Recent natural and manmade disasters demonstrated the high vulnerability and

45 unpreparedness of most communities (Alsubaie et al., 2015). Modern societies have proved to

46 be heavily dependent on their critical infrastructures, which provide essential services and

47 contribute significantly to the social and economic development (Ismail et al., 2011). Having
48 a more comprehensive insight into critical infrastructures and their mutual dependencies would
49 yield crucial information on community disaster vulnerability, which represents the sensitivity
50 of a community exposed to a given hazardous event (Cash et al., 2006).

51 Understanding the vulnerability of critical infrastructures is of paramount importance as it
52 allows to properly predict community resilience, which is defined as the ability of a system to
53 respond and recover from disaster (Cimellaro et al., 2016; Cutter et al., 2008). Among all
54 definitions of resilience, (Walker & Salt, 2006) define resilient systems as “sustaining
55 ecosystems and people in a changing world”, therefore resilience is intertwined with
56 sustainability. Resilience can be considered as one of the indicators of sustainability as being
57 resilient is essential for being sustainable (G. P. Cimellaro, 2016).

58 Current practices of infrastructure modeling incorporate both facilities (housing, commercial,
59 and cultural facilities) and lifelines (hospitals, transportation systems, power and
60 communication networks, water distribution networks, etc.) (Renschler et al., 2010). However,
61 there is still a lack of tools and methods to assess resilience at the urban level (Ribeiro &
62 Gonçalves, 2019).

63 The first step towards large-scale urban simulations is the development of standards and
64 metrics that enable decision-makers to quantify resilience. An indicator-based framework for
65 measuring urban community resilience was introduced by Kammouh et al. (2019). The
66 framework, namely *PEOPLES*, captures the overall resilience of communities considering
67 different aspects/layers, i.e., population, environmental and ecosystem, organized
68 governmental services, physical infrastructures, lifestyle, economic development, and social

69 capital. Karakoc et al. (2020) proposed an important measure that is derived by social aspects
70 of resilience to identify the most critical components that have the largest impact on the
71 performance of interdependent networks. A hybrid simulation framework was suggested by
72 Hwang et al. (2016) to plan immediate recovery measures for the regional facilities in the
73 aftermath of a disaster combining system dynamic approaches with discrete-event simulations.
74 More detailed indicator-based models have been developed for single infrastructures typical of
75 modern communities. For instance, Balaei et al. (2020) identified indicators to quantify the
76 robustness and consequently the resilience of water supply systems, which are essential in the
77 aftermath of a disaster.

78 The interaction among critical infrastructures needs to be examined to correctly model and
79 comprehensively analyze the community system. A modeling and simulation framework was
80 developed by Dudenhoeffer et al. (2006) to simulate the urban infrastructure interdependencies
81 given a flood event. Infrastructures were modeled as a network consisting of nodes and edges,
82 while interdependencies were defined as direct links between infrastructures' components.
83 Focusing on system interdependencies and related cascading effects, Guidotti et al. (2016)
84 investigated the effects of the seismic damage of an electric power network on a water
85 distribution network while Domaneschi et al. (2019) focused on the interdependency between
86 seismic damage of masonry buildings and transportation networks. In addition, a recent study
87 showed the importance of considering the pre-event conditions of interdependent stormwater
88 drainage system and road transportation network (Yang et al., 2019).

89 Recent years have seen a rise in the development of integrated platforms to quantify the
90 resilience of infrastructure systems. In their research, Repetto et al. (2017) provided tools for

91 real-time monitoring of seaports which can have a highly positive impact on improving the
92 resilience of coastal urban communities. Different applications can be found for different
93 scenarios and hazards. Among others, a conceptual integrated framework (Martí, 2014) was
94 proposed to plan and coordinate the response of multiple infrastructures during disasters.
95 Borgdorff et al. (2015) developed a software tool (SIM-CITY) to predict complex urban
96 dynamics to coordinate emergency services and urban planners. An example of a Virtual
97 Geographic Environment (VGE)-based simulation framework for flood disaster management
98 was presented by Ding et al. (2014), while a community-driven project named Global
99 Earthquake Model (GEM) (Crowley et al., 2013) simulates earthquake risks. The main goal of
100 the GEM foundation is to define standards and collect best practices related to seismic hazard
101 and risk assessment methodologies, with a focus on data collection and storage. Besides,
102 seismic vulnerability through empirical, analytical, and expert opinion was addressed by Porter
103 et al. (2012), while an open-source software named the OpenQuake (Silva et al., 2014) was
104 developed to evaluate human or economic losses.

105 Although previous studies have tackled disaster community modeling and simulation, the
106 integration of all computing resources into a unified platform remains a challenge. An
107 integrated platform would provide a more effective problem-solving approach that is useful to
108 assist the decision support system. This poses several practical challenges in enabling different
109 simulators to interact and in organizing the information system flow for a standardized output.

110 The main objective of this work is to develop an integrated platform to assess seismic
111 resilience at the community level. With this aim, new methods and computational procedures
112 are proposed. These methods are implemented in a new software tool that assesses the

113 vulnerability of critical infrastructures in large-scale urban areas. Besides, innovative physical
114 interdependency models have been implemented in the platform. As a testbed, a virtual city
115 that mimics a typical Italian building stock is designed. The information of the physical systems
116 (i.e. buildings, transportation, power, water networks) is collected in the form of a machine-
117 readable database. The designed testbed is used throughout the manuscript to explain the
118 different methodologies introduced in this paper; thus, there will not be a separate section
119 dedicated to the methodologies.

120 The entire analysis is controlled in a Python-based environment implementing a parallel
121 computing workflow. The developed software comprises different Python classes that include
122 all necessary algorithms to assess the building portfolio damage and model the physical
123 interdependencies within and across the networks. The software tool includes visualization
124 methods that convert the numerical results into easy-to-interpret figures which can be crucial
125 for decision-makers. Resilience and interdependency analyses, which this paper is centered
126 around, help decision-makers to identify vulnerable structures and infrastructure prior to the
127 event so they can develop sustainable technologies for preparedness and reconstruction.

128 The rest of the paper is organized as follows. Section 2 gives an overview of the proposed
129 hybrid community model. Section 3 presents the details for modeling and simulating the
130 building portfolio. Section 4 describes the methods used for modeling the road infrastructure
131 network and for analyzing its interdependency with the building stock. Sections 5 and 6 deal
132 with the power system and water distribution network, respectively. In section 7, the agent-
133 based model used to simulate the socio-technical network is introduced. Section 8 presents an
134 application of the entire computational procedure considering different seismic scenarios to

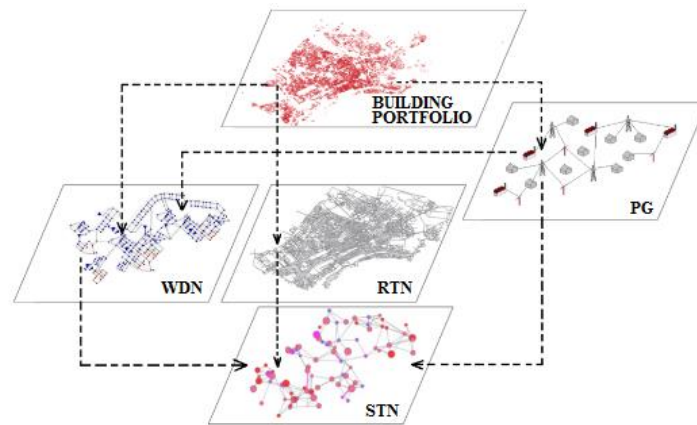
135 demonstrate the platform's features and functionality. Finally, conclusions are drawn in Section
136 9.

137 **2. HYBRID COMMUNITY MODEL**

138 Community vulnerability modeling is multi-layered as it considers the responses of different
139 infrastructures and social networks, including their interdependencies (Pamungkas et al.,
140 2014). Common approaches can be grouped into six types: empirical, agent-based, system
141 dynamics, economic theory-based, network, and others (Ouyang, 2014). Empirical approaches
142 analyze the system's components according to historical disaster data. In agent-based
143 approaches, the system is considered as adaptive and its complex behavior is described as the
144 interaction of autonomous agents (Cimellaro et al., 2017). System dynamic approaches attempt
145 to model the evolutionary behavior of interdependent infrastructures by capturing causes and
146 effects under an external impact. On the other hand, network-based approaches model each
147 infrastructure combining nodes and links, while the interdependencies among infrastructures
148 are defined using interlinks. Finally, economic theory-based approaches focus on market rules
149 to model interdependencies. Other approaches include Bayesian networks, hierarchical
150 methods, and hybrid models. The latter result from a combination of two or more traditional
151 methods (Kammouh, Noori, et al., 2018).

152 In this work, a hybrid model is proposed to couple Network Models (NMs), which are used
153 to analyze the physical infrastructures, with Agent-Based Models (ABMs) to simulate the
154 socio-technical networks (emergency rescue services, firefighters, etc.). It is applied to a virtual
155 city named *Ideal City*, which is envisioned as being representative of a typical European urban
156 area and it is inspired by the city of Turin in Italy. Its building portfolio comprises four different

157 sectors including housing (residential building, hotel, shelter), education (school, university,
158 library), business (shopping centers, retail stores, heavy industries), and public services
159 (hospital, police station, churches, airport, etc.). Figure 1 schematically shows the hybrid multi-
160 layered model of *Ideal City* and the interdependencies among the networks. Four lifelines
161 supporting the community's demands are modeled: (i) the Road Transportation Network
162 (RTN), (ii) the Water Distribution Network (WDN), (iii) the Power Grid (PG), and (iv) the
163 Socio-Technical Network (STN). The proposed hybrid model takes into account also cascading
164 effects between the building damage and the RTN, the PG, the WDN, and the STN in the
165 aftermath of an earthquake.



166

167 **Figure 1.** Hybrid multi-layered model and interdependencies (dashed arrows).

168 The dashed lines refer to the interdependencies between layers that have been modeled in the
169 proposed platform. The damage experienced by the building portfolio is considered as the
170 trigger event inducing an additional loss of functionality in all the remaining networks (RTN,
171 WDN, PG, and STN). Moreover, the functionality of WDN is dependent on the PG due to the

172 presence of pumps and electric valves. The functionality of all the considered physical
173 networks affects the STN response (e.g. emergency rescue and evacuation, human behavior).

174 **3. MODELING THE BUILDING PORTFOLIO**

175 Performing urban large-scale simulations, some generalizations and simplifications on the
176 building portfolio are necessary to overcome the lack of data and to limit the computational
177 workflow. Therefore, a *surrogate* model to describe the lateral behavior of each building is
178 herein adopted by considering the relationship between its base shear and top horizontal
179 displacement (Marasco et al. (2017); Noori et al. (2017)). The lateral stiffness properties are
180 modeled through a parameterized backbone curve, where the post-elastic line is characterized
181 by progressive decreasing stiffness, while hysteresis is accounted through the Takeda model
182 (Takeda et al., 1970).

183 **3.1 Building exposure database**

184 An essential advantage of the *surrogate* model is the limited computational effort it requires
185 with respect to a more refined finite element model, providing a significant benefit for large-
186 scale urban simulations. However, it presents several practical challenges because detailed
187 information about each building is generally not available. To overcome this issue, different
188 methods have been proposed to classify the building stock based on their typical characteristics
189 (Crowley et al., 2013; Lu & Guan, 2017). Although rapid, these methods are not so accurate
190 because they could give similar results for buildings with different structural characteristics.

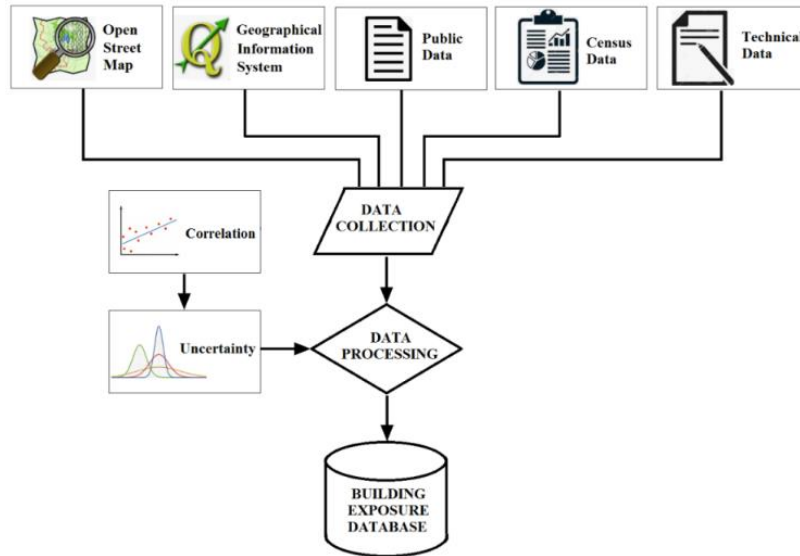
191 The approach proposed herein can collect data from different public and accessible sources.
192 Based on the building stock of the city of Turin, general geometrical parameters (e.g., footprint
193 area and total height) have been obtained from OpenStreetMap (Haklay & Weber, 2008), while

194 more detailed information (e.g., number of stories, year of construction) have been found in
195 Geographical Information Systems (Maguire, 1991). Besides, further public information
196 (provided by Municipality or other authorities), census data (provided by National or regional
197 Statistical Institute, ISTAT (2016)), and other technical information (e.g. real estate data,
198 design guidance) have been exploited to increase the level of knowledge.

199 Data analysis has been performed to identify common patterns; e.g. building's age has been
200 correlated with the adopted design methods and parameters (e.g. load combinations and
201 material strength classes), which has been used to estimate the minimum required geometrical
202 and mechanical characteristics of the structural components. However, this procedure may lead
203 to discrepancies with real data. Therefore, uncertainties characterization has been introduced
204 to face the statistical nature of data, considering the buildings' parameters as normally
205 distributed Random Variables (RVs).

206 Correlation among the different variables used in the analysis may also exist. In this study,
207 the correlation between the reinforcement percentage and the characteristic reinforcing bar
208 yield strength has been considered according to the Probabilistic Model Code (Vrouwenvelder
209 & Faber, 2001). Also, a correlation between characteristic compressive strength and the elastic
210 modulus of the concrete (Mirza & MacGregor, 1979) has been considered assuming a
211 correlation coefficient of 0.8.

212 The flowchart of the data analysis is shown in Figure 2. Sources are illustrated on the top of
213 the scheme as they contribute to the data collection phase. Then, correlations among the
214 variables are considered in the data processing phase, and, finally, the processed data are stored
215 in a standard format to create a comprehensive building exposure database.



216

217

Figure 2. Flowchart of data analysis.

218 **3.2 Backbone curve estimation**

219 Each building is modeled as Multi-Degree-Of-Freedom (MDOF), which is subjected to a
 220 monotonically increasing lateral force distribution proportional to its fundamental mode.
 221 Elastic parameters are identified by the values of base shear and top displacement that cause
 222 the yield of the weakest column. Post-elastic parameters are assessed based on the upper-bound
 223 theorem of limit analysis and the equal energy rule (Marasco et al., 2017). These parameters
 224 allow to define a backbone curve representative of an equivalent Single-Degree-Of-Freedom
 225 (SDOF) model for each building. Four-point and three-point parametrized backbone curves are
 226 adopted for RC and masonry buildings, respectively.

227 All building's parameters that are significant to predicting the global structural capacity are
 228 assumed lognormally distributed RVs. Each statistical distribution is represented by the median
 229 (μ) and dispersion value (σ). The latter is based on the completeness of the quality and
 230 confidence associated with the building parameter that depends on its level of knowledge. In

231 the proposed methodology, three classes of building parameters are identified that are:
 232 mechanical-based (M), geometrical-based (G), and construction-based (C). For each class, a
 233 certain standard deviation has been set based on the building archetype and year of construction
 234 (Table 1).

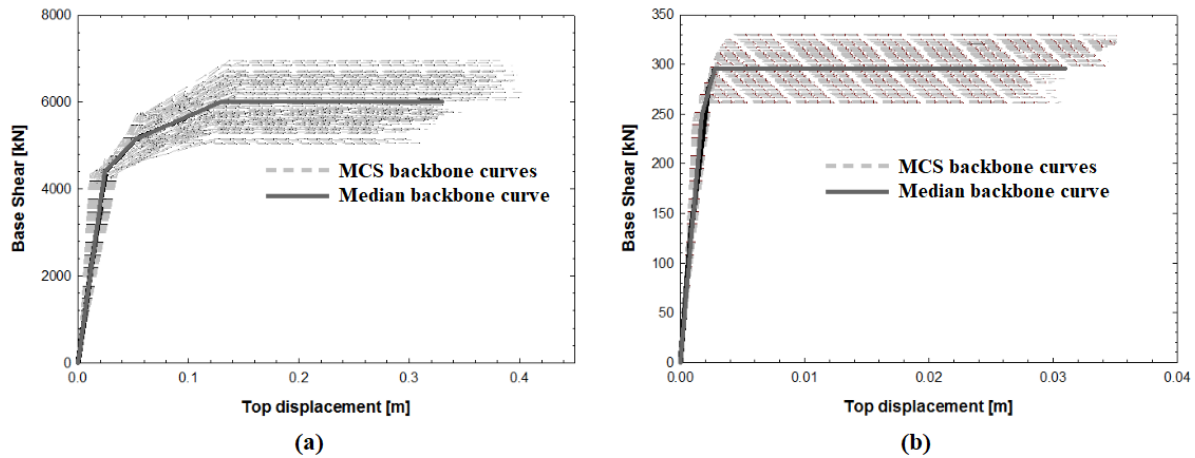
235 **Table 1.** Standard deviations associated with the mechanical, geometrical, and
 236 construction-based parameters for RC and masonry buildings based on the year of
 237 construction.

		Year of construction					
		< 1916	1916-1937	1938-1974	1975-1996	1996-2008	> 2008
RC	σ_G/μ_G	0.20	0.18	0.16	0.13	0.1	0.08
	σ_C/μ_C	0.25	0.22	0.20	0.18	0.15	0.10
	σ_M/μ_M	0.20					
Masonry	σ_G/μ_G	0.25	0.22	0.2	0.17	0.13	0.10
	σ_C/μ_C	0.28	0.26	0.24	0.22	0.20	0.18
	σ_M/μ_M	0.25					

238
 239 The standard deviation values are higher for old buildings since some of the building
 240 information lack of precision. Furthermore, a larger standard deviation is found for masonry
 241 buildings. The mechanical parameters refer to the compressive and tensile strength and elastic
 242 modulus of the constitute materials (concrete, bricks, stones, steel rebar), while the geometrical
 243 parameters are represented by the dimensions of the structural components (e.g. span length,
 244 cross-section width and depth, percentage of reinforcement). Finally, the construction-based
 245 parameters comprise all those variables that affect the building design such as the vertical and
 246 horizontal loads and the type of deck and external walls. The building data collection has been
 247 discussed in detail in the previous section.

248 The backbone curve is computed for each single building by varying its parameter through
 249 Monte Carlo Simulation (MCS) in the range $\mu \pm \sigma$. The iterative process ends when the output

250 dataset is consistent and provides a stable estimate of the median backbone curve which
251 represents the global building's capacity. As 7-story RC and 4-story masonry buildings built
252 in 1930 and 1978, respectively have been considered. The estimated median backbone curve
253 for the RC and masonry buildings have been illustrated in Figure 3.



255 **Figure 3.** Backbone curves obtained through MCS and estimated median backbone curve
256 for (a) RC and (b) masonry buildings.
257

258 3.3 Nonlinear time history analyses

259 Structural analyses have been carried out through the finite element code OpenSees (Mazzoni
260 et al., 2006). Recent advances have been introduced by Zhu et al. (2018) to offer multi-
261 interpreter capabilities resulting in the release of an “OpenSeesPy” library in Python. It has
262 been used to implement the *surrogate* model and to perform the nonlinear time history
263 analyses.

264 Each building has been modeled as “ZeroLength” element through two overlapped nodes.
265 Initial stiffness and proportional damping corresponding to the median backbone curve are
266 assigned to each element in both horizontal directions. Uniaxial “MultiLinear” material is
267 employed to simulate the force deformation relationship, while the Takeda model is adopted

268 to consider the hysteresis. Seismic input consists of a pair of time histories (in both horizontal
269 directions) applied at each element's location.

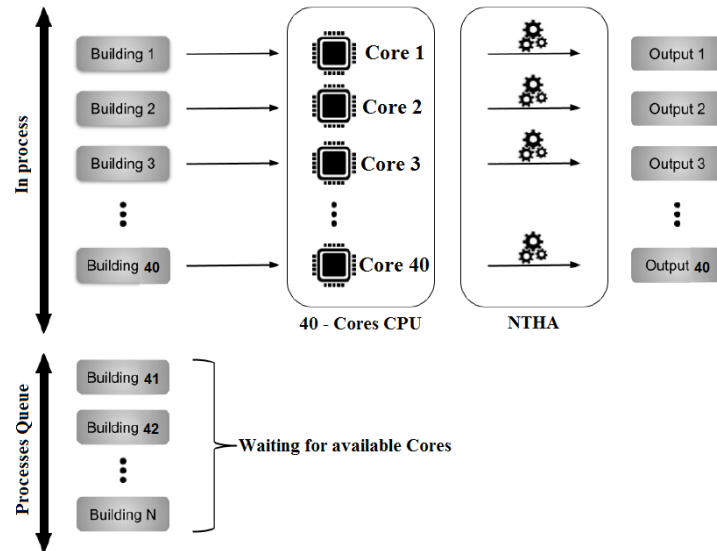
270 A simplified seismic scenario is assumed by defining epicenter location, moment magnitude,
271 and time history recorded in the epicenter. Seismic inputs at any building locations are
272 estimated based on Ambraseys' ground motion model (Ambraseys et al., 1996), while
273 frequency changing is neglected. Therefore, nonlinear time history analyses are performed and
274 the maximum top displacements of each element are computed.

275 **3.4 Multiprocessing computation**

276 Advancements in computer knowledge and architecture have led to the development of
277 algorithms that can speed up the entire computational process through parallelization
278 techniques. In parallel and distributed systems, Graphics Processing Unit (GPU) or Central
279 Processing Unit (CPU) solvers can be adopted. GPU solvers exploit the high computation
280 power of NVIDIA CUDA (Kirk, 2007) to significantly decrease the simulation time.
281 Numerical GPU algorithms can be substantially accelerated as long as the algorithms map well
282 to the specific hardware's features. For limited bandwidth problems that do not aim to the
283 solution of a large complex matrix, the GPU solution might not be optimal because it causes
284 poor or negative speedups (Ament et al., 2010). Thus, CPU-solvers may be adopted using
285 parallel programming based on *threading* and *multiprocessing* processes. The first process
286 consists of breaking the process within different parts while running the tasks that have access
287 to the same memory areas. Instead, multiprocessing consists of submitting multiple processes
288 independently to separate memory locations. The main advantage of multiprocessing is that it
289 avoids conflicts in case the processors are assessing the same memory location at the same

290 time; therefore, it is appropriate for distributed memory systems with several CPU processors
291 (e.g. supercomputers).

292 Given the considerations above, in the present study, the multiprocessing Python standard
293 library has been used. The nonlinear time history analysis of each building has been assigned
294 to different memory locations (Figure 4). A Rack Server with no. 2 Intel Xeon (E5-2698 v4
295 2.2GHz, 50MB Cache) and 256 GB RAM (8x32GB DDR4, 2400MHz) has been employed in
296 this study. A schematic representation of the procedure used to speed up the processes is shown
297 in Figure 4.



298

299

Figure 4. Multiprocessing scheme.

300

301

302

303

4. ROAD TRANSPORTATION NETWORK (RTN)

304 Road infrastructure connectivity within and among communities is essential to provide
305 services and to forward social and economic growth. This topic has inspired several studies
306 that developed different tools to investigate properties of large-scale transportation networks,
307 from Python packages like NetworkX (Hagberg et al., 2008) to open source software such as
308 Gephi (Bastian et al., 2009). Graph theory principles are certainly one of the most frequent
309 tools in this field due to their simplicity and effectiveness to solve problems related to routing,
310 traffic, minimum cost flow, etc.

311 *Ideal City's* road transportation network (RTN) has been modeled as an undirected graph G
312 (each path can be passed through in both directions) that consists of 14,239 nodes (N),
313 representing the road's intersections, and 18,798 edges (E), i.e. the links. Despite road maps are
314 directed graphs, as streets have a certain directionality, the choice of modeling the system as
315 an undirected graph has been followed because, in emergency conditions, directionality is not
316 respected to give priority to evacuation and rescue operations.

317 Theoretically, the network has been described with an $N \times N$ adjacency matrix A . The
318 elements inside A can be either 1 or 0. If $a_{i,j} = 1$, it means that node i and node j are connected,
319 while $a_{i,j} = 0$ means that nodes i and j are disconnected. Since the graph is not directed, the
320 resulting adjacency matrix is symmetric. The adjacency matrix allows computing many
321 network parameters and quickly modifying the topology of the network, e.g. when roads are
322 unavailable. An important global metric of graphs is the *average vertex degree* ($\langle vd \rangle$), which
323 indicates how many edges cross a given node (Equation (1)).

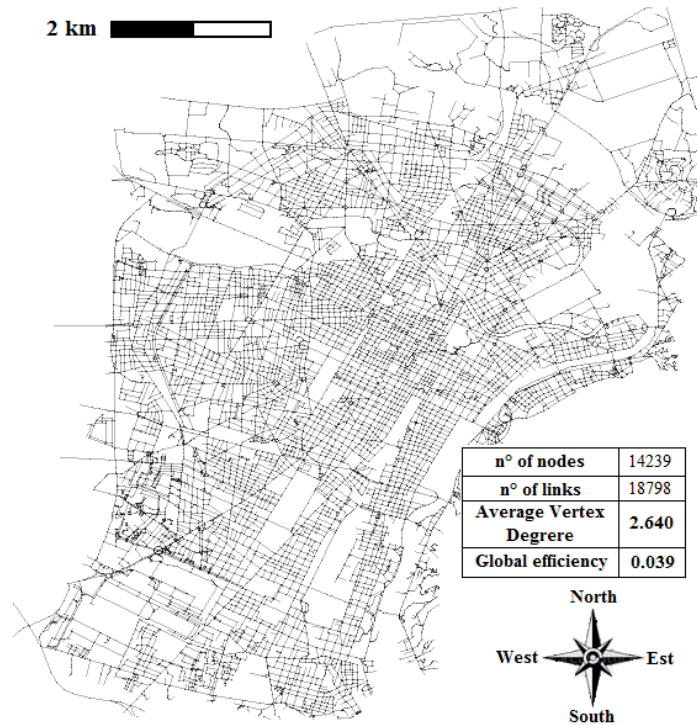
$$\langle vd \rangle = \frac{1}{N} \sum_{i \in N} \sum_{j \in N} a_{ij} \quad (1)$$

325 In the case of an undirected graph, edges crossing a node should be considered only once,
326 thus the adjacency matrix becomes triangular.

327 *Global efficiency* is another measure of network performance that was introduced by Latora
328 and Marchiori (2001). It is defined as the average of the number of edges $d_{(i,j)}$ in the shortest
329 path between nodes i and j (Equation (2)):

$$330 \quad E_{glob} = \frac{1}{N(N-1)/2} \cdot \sum_{i \neq j} \frac{1}{d_{(i,j)}} \quad (2)$$

331 The plan view of the RTN with its main properties is shown in Figure 5.



332

333 **Figure 5.** *Ideal City's* RTN plan view.

334 **4.1 Interdependency between buildings and RTN**

335 The interdependency between buildings and the RTN following an earthquake is caused by
336 the amount of the debris generated from the buildings' damage. To assess the amount of

337 generated debris, pictures collections by reconnaissance groups in the aftermath of worldwide
338 seismic events have been used. These collections belong to publicly available databases: the
339 Earthquake Engineering Research Institute clearinghouse and collection of case studies
340 (EERI), the Geotechnical Extreme Events Reconnaissance (GEER), and the Digital
341 Environment for Enabling Data-Driven Science (DEEDS) ones. Despite that these valuable
342 sources contain thousands of images, only a small percentage clearly shows the amount of
343 generated debris that can be measured. So after visual inspection, a database of 195 pictures
344 has been selected.

345 Each selected picture shows a building suffering a partial or complete collapse after a seismic
346 event. In total, 14 different earthquakes on different world regions have been considered, i.e.,
347 Central Italy (38 pictures), Cephalonia (6 pictures), South Napa Valley (6 pictures),
348 Christchurch (9 pictures), Ecuador (32 pictures), Nepal (38 pictures), India (6 pictures), Loma
349 Prieta (5 pictures), Central Mexico (20 pictures), North Iran (1 picture), Northridge (2 pictures),
350 Armenia (5 pictures), Taiwan (26 pictures), Turkey (1 picture).

351 In the first step, the following information has been collected: (i) the earthquake magnitude,
352 (ii) the epicentral distance, and (iii) the year of construction, (iv) the building archetype, (v) the
353 building height and (vi) the number of stories. Then, each picture has been visually inspected
354 to identify objects, such as vehicles, whose dimensions can be estimated. Starting from these
355 reference measures, the extension of the debris with acceptable accuracy has been evaluated
356 (Figure 6). Let P be the dimension of a reference object and p the debris' extension measured
357 in pixel (px). Let D and d be the corresponding measures in m of the reference object and the
358 debris extension, respectively. The debris extension d can be computed using

359 Equation (3).

$$360 \quad d = p \cdot \frac{D}{P} \quad (3)$$

361 Then d is normalized by the building height to reduce its variance, allowing an easier
362 comparison across different models.



363

364 **Figure 6.** Example of debris extension evaluation.

365

366 Then, two machine learning (ML) algorithms have been considered: Random Forest (RF),
367 and k-Nearest Neighbors (KNN) algorithm (Liaw and Wiener (2002), Piegl and Tiller (2002)).
368 The KNN algorithm predicts a new data point starting from the closest data in the training
369 datasets, i.e. its “nearest neighbors” (Ni & Nguyen, 2009). Where ‘k’ stands for how many
370 samples are used to evaluate the prediction. An RF, instead, is essentially a collection of
371 randomized decision trees (Yao et al., 2011). The idea behind RFs is that multiple trees might
372 reduce the problem of overfitting with respect to a single decision tree. There are two ways in
373 which the trees in a random forest are randomized: by selecting the data points used to build a
374 tree and by selecting the features in each split test.

375 Both selected algorithms have been tuned to obtain the optimal result and accuracy. In the
376 KNR algorithm, the tuned parameter is the number of neighbors taken into consideration to
377 evaluate the predictions in a χ test. This parameter k has been set equal to 5. Instead in RF,
378 three parameters have been tuned: (i) the maximum depth of the tree (set to 10), (ii) the number
379 of trees in the forest (set to 20), (iii) the minimum number of samples required to split an
380 internal node (set to 40).

381 The two algorithms have been used to estimate the extension of debris and they have been
382 compared using the R-squared and the mean absolute relative distance (MARD).

383 The R-squared measure provides a measure of how well future samples are likely to be
384 predicted by the model by evaluating how much the scatter points are distant from the
385 regression fit line calculated by the algorithm. R-squared measure ranges from 0 to 1, where 1
386 means perfect matching. MARD is the average vertical distance between each point and the
387 regression line. Therefore, the lower the value of MARD and the more accurate the predictions.

388 Results from the training of the algorithms show that KNR algorithm gives a better MARD
389 score (0.32), but a lower value of R-squared (0.42) with respect to RF, which means that more
390 data are needed for KNR. Instead, RF gives better results both in terms of R-squared (0.52)
391 and MARD (0.22) and therefore this algorithm has been selected and implemented in the
392 platform.

393

394

5. POWER GRID

395 Urban PGs consist of a transmission system, which runs for long distances at high voltages,
396 and a distribution system, which delivers electricity at medium and low voltage. The low

397 voltage line (i.e. 230 V single-phase, 400 V three-phase for European countries) supplies
398 domestic and small commercial customers. Usually, at the city-level, PGs follow the main
399 streets and may run both overhead and underground.

400 Various methodologies are available in the literature to assess the seismic damage to the
401 electric infrastructure (Cavalieri, Franchin, Buriticá Cortés, et al., 2014). However, they require
402 a large amount of data about the network's components, which is often not shared by
403 stakeholders and public authorities.

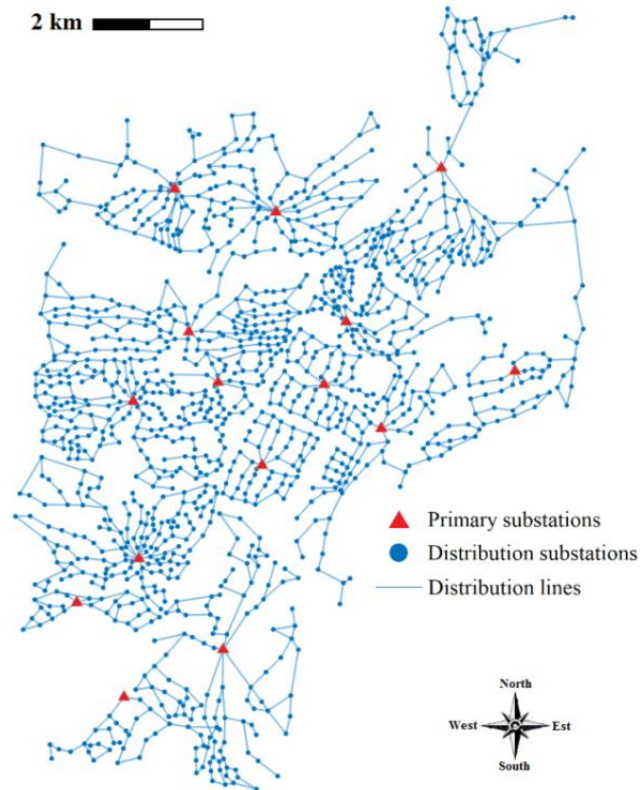
404 Moreover, most of these methods assess the resilience of power distribution networks
405 adopting the inherent fragility of the electrical components. However, in most cases, electrical
406 components can withstand seismic excitation, while the buildings where they are installed are
407 subject to serious seismic damages. The debris generated from partial or complete collapses
408 damages electrical components, compromising the functionality of the entire PG. The weakest
409 element of PGs are often distribution substations as discussed in Fujisaki et al. (2014). Fragility
410 of substations varies whether their components are anchored or unanchored. Cavalieri,
411 Franchin, and Pinto (2014) reported a complete overview of the main recent works on fragility
412 functions of electric power system components, with the indication of the methodology used
413 to evaluate the curves, the components considered and the damage states and indices.
414 Considering the HAZUS methodology (Agency, 2003), to have extensive level of damage (i.e.,
415 repairs needed to restore functionality), the median peak ground acceleration (PGA) should
416 reach 0.34g for low voltage substations with unanchored components and 0.45g in case of
417 anchored components. These values of PGAs are most likely to cause serious building damage
418 given the typical built environment of European cities. Therefore, in this paper, the

419 vulnerability of the PG is related to the damage occurring to the buildings where substations
420 are located. In other words, if the building where a substation is installed collapses, the grid
421 components in that substation fail. Consequently, when a substation fails the electric load drops
422 to zero, and all the buildings connected to that substation are without power.

423 The fragility of distribution lines has not been considered since at the urban level distribution
424 lines are more robust than distribution substations. Distribution lines can run both overhead
425 and underground, despite modern cities prefer to let the system run underground as it is safer
426 and more efficient. In Ideal City, they are mainly meant to be underground. Generally, failure
427 of underground lines happens only in case of strong shakes with significantly large ground
428 deformations, which would cause serious building damage anyway. On the other hand,
429 overhead distribution lines are mostly affected by strong winds, while their vulnerability to
430 earthquakes is limited due to the small size and slenderness of urban utility poles.

431 Ideal City's PG consists of 15 primary substations and 1274 distribution substations (Figure
432 7). The primary substations operate at high and medium voltages and are supposed to be

433 located in robust facilities so that they can keep operating even after strong ground motions.



434

435

Figure 7. *Ideal City's* PG.

436

437 **5.1 Interdependency between buildings and PG**

438 The power system of *Ideal City* has been modeled following the *Density Design Method*

439 (DDM) proposed by Cardoni et al. (2019). The DDM is based on the idea that the fragility of

440 electric substations is the same as the buildings hosting them. Therefore, the electric

441 components and the buildings where they are located are assumed as a series system with their

442 corresponding fragility functions, so the weakest component limits the overall system

443 reliability. This approach allows to implicitly take into account the interdependency between

444 the power network and the building portfolio. The DDM allows for a detailed analysis of the

445 system, as the PG is specifically designed instead of using an existing database. Thus,
 446 population density, power load density, and system properties (e.g., feeders' length, load types,
 447 buses' redundancy, etc.) are the main design parameters. The first step consists in dividing the
 448 area covered by *Ideal City* into districts to locate primary substations. These are characterized
 449 by a medium voltage (MV) scheme of 22 kV. Then, electrical loads are identified following
 450 the procedure described by the 2016 European guidelines (Prettico et al., 2016). Based on the
 451 area and population of each district, the design load is estimated. In detail, the adopted design
 452 load density is assumed to be 8 MVA/km² for each district. This information is needed to
 453 identify the distribution substations containing transformers. Transformers can be of three
 454 types, i.e., 0.40 MVA, 0.63 MVA, and 1.00 MVA. The chosen distribution is 60%, 30%, and
 455 10% respectively, in accordance with current best practices. Overall, *Ideal City*'s PG consists
 456 of 1,274 distribution substations. Table 2 summarizes the number of distribution substations
 457 for each power category.

458 Table 2. *Ideal City*'s distribution substations.

Distribution substation type	Total number
0.40 MVA	766
0.63 MVA	382
1.00 MVA	126

459
 460 Distribution substations are evenly located in the district considering power demand so that
 461 each of them supplies a different number of buildings. Substations located in buildings that are
 462 extensively damaged or collapsed after an earthquake are assumed to fail. Besides, since the
 463 distribution substations are connected in series, once a substation fails all the downstream

464 substations will also be unfunctional. Consequently, the number of buildings and users not
465 supplied after the seismic event can be determined.

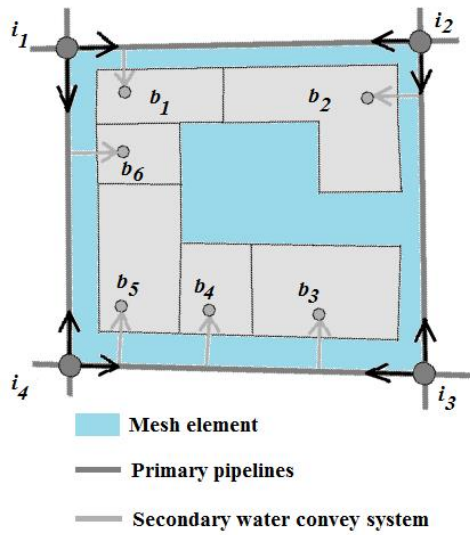
466 **6. WATER DISTRIBUTION NETWORK (WDN)**

467 The WDN serviceability implies enough water supply to fulfill the demand and reasonable
468 water pressure. The damages induced by seismic events are likely to cause a drop in the water
469 pressure and consequently a limited water supply.

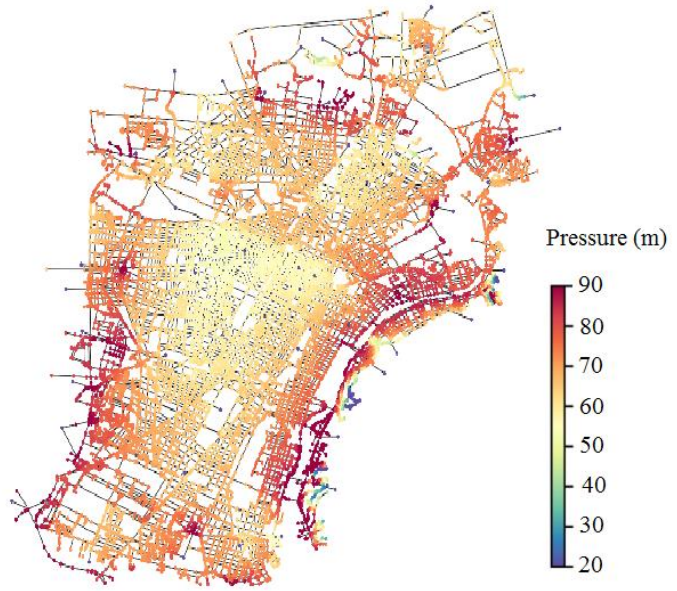
470 In this research, urban water consumption is extrapolated from national census data and the
471 layout of the WDN of *Ideal City* has been assumed to overlap the RTN. Elevations of WDN's
472 nodes have been gathered from Google Maps (Svennerberg, 2010). Collected data have been
473 processed through the Water Network Tool for Resilience, which is a Python package designed
474 to simulate and analyze the resilience of water distribution networks. This tool allows
475 controlling EPANET 2.0 (Rossman, 2000) using Python.

476 The water demand at each node (junction) depends on the number of people served by that
477 node. The number of the population served by each node has been estimated from the number
478 of households around that node.

479 Water distribution systems consist of interconnected components including primary and
480 secondary pipelines, storage facilities, and components that convey water on buildings based
481 on the closest distance between the primary pipeline and the buildings inside the mesh (Figure
482 8a).



(a)



(b)

483

484 **Figure 8.** (a) Water demand in w^{th} element, i^{th} nodes of the element, and water convey on

485 buildings within the element. (b) Water pressure of the WDN after calibration.

486

487 The calibration of a WDN of such a size brings on several difficulties. It is a fundamental

488 issue to ensure an accurate and realistic simulation for both the flow velocity and pressure. The

489 pipes diameters and the positions of the valves, pumps, reservoirs, and tanks have been

490 determined to ensure the following constraints (Equations (4),(5)):

$$491 \quad 0.5m/s \leq \text{Velocity} \leq 2m/s \quad (4)$$

$$492 \quad 40m \leq \text{Pressure} \leq 80m \quad (5)$$

493 Figure 8b shows the calibrated WDN at the peak hour of water demand. More details about

494 the network's generation methods and technical criteria can be found in (Taurino et al., 2018).

495

496 **6.1 Vulnerability of the WDN**

497 The reliability of a water network is connected to the concept of vulnerability of its elements.
498 Herein, the focus is given to the pipe because it is the most challenging component to inspect
499 and replace, and also its extensive distribution and exposure make it especially vulnerable. In
500 this work, the seismic vulnerability of the buried pipelines introduced in the American Lifelines
501 Alliance (Eidinger et al., 2001) is adopted.

502 The seismic wave propagation induces strains to the pipes due to the soil-pipe interaction.
503 Strains could produce damage if the pipe strength is exceeded. When pipe damage occurs, the
504 pipe is assumed to break in the middle. In the context of this work, only major damage is
505 assumed to cause water leakage. Pipe damage is modeled dividing the pipe into two equal parts.
506 Then two reservoirs are added at their endpoints to simulate the water leakage through the
507 crack. The reservoirs have a total head equal to the elevation of the middle point of the pipe
508 (assuming that the pipe breaks in the middle). A check valve is inserted so that water only flows
509 towards the reservoirs.

510 A combined demand-driven and pressure-driven analysis is conducted to account for the
511 dependence of water supply on pressure. First, a Demand-driven analysis is performed; then,
512 nodes with pressure below the value required to satisfy the demand are converted into Emitter
513 nodes.

514 **6.2 Interdependency between buildings and WDN**

515 Once a seismic event occurs, an additional drop of pressures might be considered due to the
516 damage to the secondary water system. In this study, a further drop of pressure in the pipelines
517 system is considered when “extensive” or “complete” damage occurs in a household located

518 within the closed-shaped WDN. In other words, the building damage scenario is used to update
519 the water supply of the WDN.

520 **6.3 Interdependency between PG and WDN**

521 The functionality of WDN is dependent on the power system due to the presence of pumps
522 and electric valves. In the aftermath of a seismic event, a power outage may occur leading to a
523 temporary inoperability of the electric device of the WDN. In this study, the interdependency
524 between PG and WDN is taken into account by identifying the unpowered pumps and then
525 updating the EPANET model accordingly. A new state of nodal pressure and water supply is
526 then generated.

527 **7. EMERGENCY EVACUATION MODELLING**

528 The implemented platform includes STN that consist of an agent-based model (ABM), which
529 can manage 900,000 individual agents that dynamically interact with each other and with the
530 urban scenario. Furthermore, the ABM can be used to model other objects, such as shelters,
531 hospitals, and ambulances that are governed by different rules. Therefore, an emergency
532 evacuation can be simulated, and specific emergency plans can be designed to study and
533 improve the community response.

534 The ABM layer is also able to manage the interdependency between the agents and the other
535 layers (i.e. the built environment, the generated debris, and the road network). Furthermore, the
536 evacuees have been implemented with individual characteristics including human behavior and
537 considering different levels of agent health obtained from the seismic damage simulation.
538 Figure 9 reports evacuating agents, where the level of injury severity is associated with the

539 agent color (e.g. green normal conditions, orange slight injured), and the evacuation velocity
540 depends on the injury level.



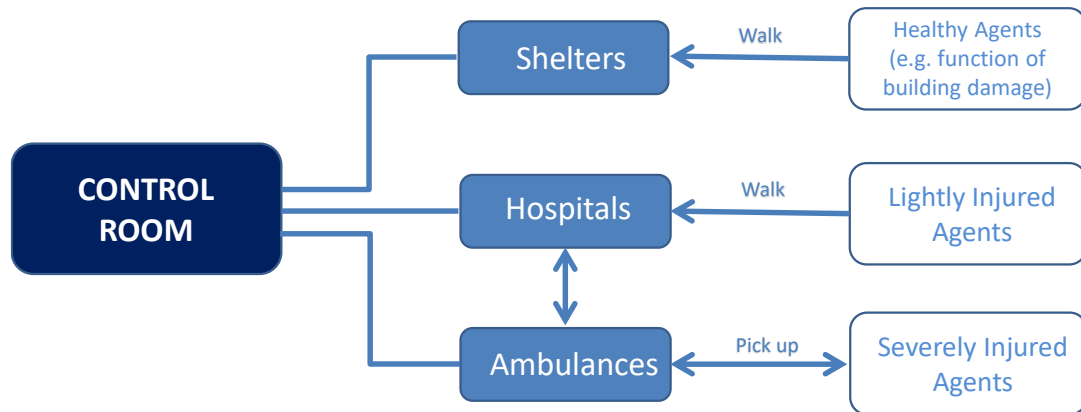
541

542 **Figure 9.** Simulation of an evacuation procedure using virtual reality. The color of each
543 agent indicates her health conditions.

544 The ABM environment has been developed in Unity (UnityTechnologies, 2020). The input
545 data needed to develop the ABM scenario are collected from the other infrastructure layers
546 implemented in the platform. Indeed, the data collected are: (i) the estimated post-disaster
547 building damage that reflects in (ii) number of injuries and (iii) road blockage due to debris.

548 **7.1 First aid modeling**

549 The ABM STN layer considers two classes of agents, the individuals, and the ambulances;
550 the last ones pick up severely injured individuals and transport them to hospitals. On the
551 contrary, lightly injured agents preserve their walking capabilities and reach hospitals on their
552 own (Figure 10). Healthy agents can remain close to their buildings or walk to the nearest
553 emergency shelter accordingly to a random procedure that is parameterized as a function of
554 damage level suffered by the buildings.



555

556

Figure 10. First-aid organization in the ABM layer.

557 Shelters have a fixed capacity, beyond which the individual starts walking toward the closest

558 town exit. Also, hospitals have a fixed capacity, except for those that can deploy a field hospital.

559 In this case, an infinite capacity is assumed to guarantee assistance to all injured individuals.

560 A control room manages the hospitals and shelters monitoring the available information and

561 making decisions about resources. The buildings may contain a number of individuals and

562 contain a variable number of individuals function of the time of the day.

563 7.2 Modeling human behavior and emotions in ABM

564 During the emergency evacuation, two frequent individual phenomena can be recognized:

565 the leader-follower and the emotional (e.g. altruism, panic) behavior. The first one is

566 recognized as the static and predictable component because it remains unchanged throughout

567 the process. Instead, the second one, the dynamic component, is generally unpredictable

568 because characterized by emotions. It can be modeled using the Belief-Desire-Intention (BDI)

569 model and implemented through a matrix approach by the Extended Decision Field Theory

570 (EDFT) to cope with the dynamically changing environment (G. P. Cimellaro et al. (2019), G.

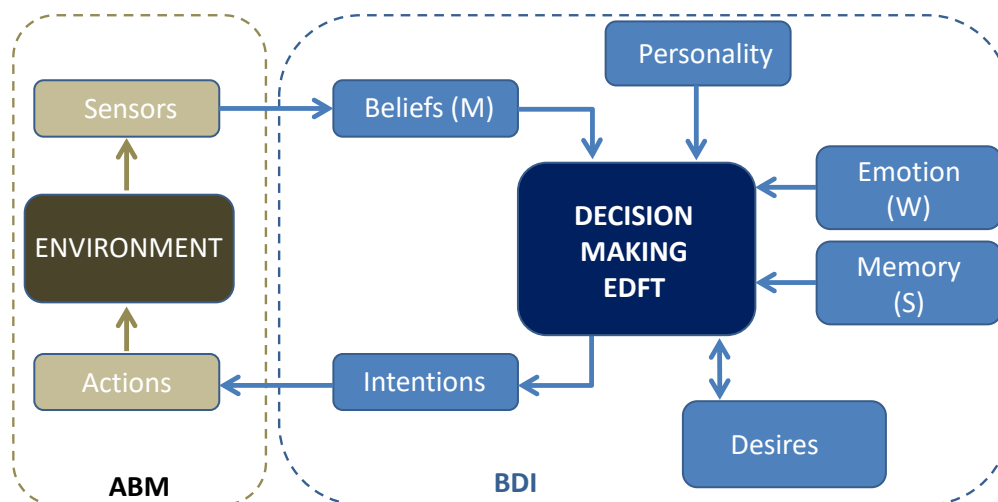
571 P. Cimellaro et al. (2017)). It presents a dynamic and probabilistic mathematical approach to

572 reproduce the individual decision-making process in the changing environment. It is
 573 summarized by the following relation that allows to compute the preferences P among m
 574 options expressed by an agent during the simulation time (Equation (6)).

$$575 \quad P(t+h) = SP(t) + CM(t+h) \cdot W(t+h) \quad (6)$$

576 where $P(t)^T = [P_1(t), P_2(t), \dots, P_m(t)]$ are the preference in percentage and $P_i(t)$ is the strength
 577 of the preference corresponding to option i at time t . The first term is the product of the
 578 preference chosen at the previous state and the stability matrix S that provides the memory
 579 effect. The second term reproduces the emotional individual behavior in the changing
 580 environment, where M is the value matrix that represents the subjective evaluations
 581 (perceptions) of a decision-maker, W is the weight vector that allocates the weights of attention
 582 corresponding to each attribute of M , and C is the contrast matrix that compares the weighted
 583 evaluations of each option. Matrix C is the identity matrix if each option is evaluated
 584 independently (G. P. Cimellaro et al. (2019), G. P. Cimellaro et al. (2017)).

585



586

587 **Figure 11.** EDFT architecture and interaction of the human behavior modules (adapted
588 from G. P. Cimellaro et al. (2019).

589
590 **7.3 Interdependencies with other networks**

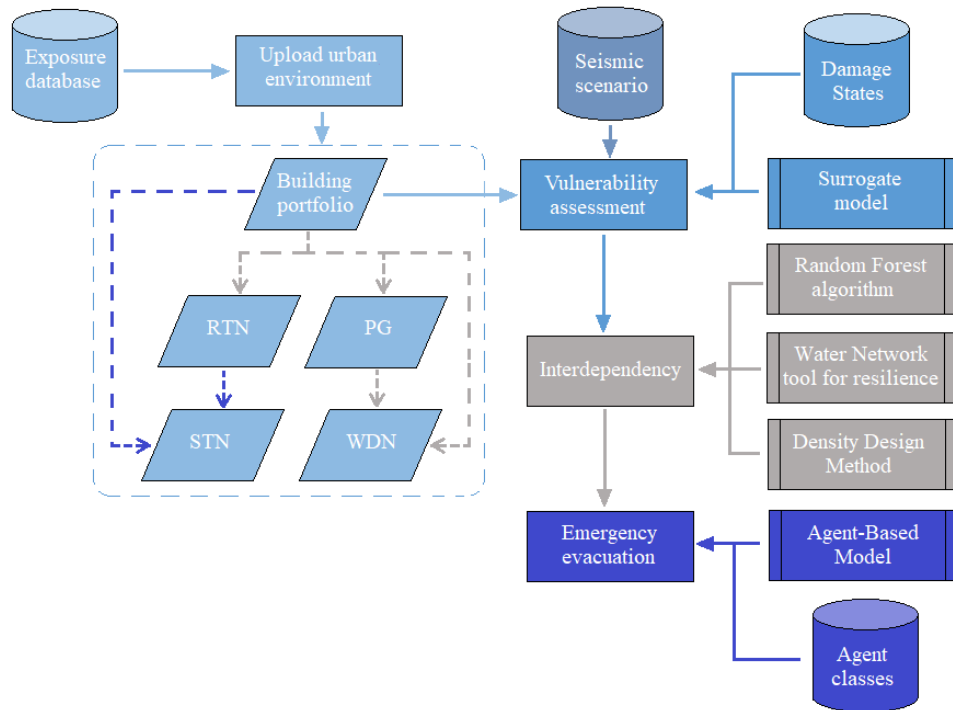
591 The interdependency between the evacuees and the built environment consists of the debris
592 generated by the earthquake-induced damages to buildings. As a cascading consequence of
593 debris accumulation, the road network can be interrupted entailing an overall increase in the
594 average number of people who have difficulty evacuating and an essential risk that some
595 individuals cannot evacuate at all. Furthermore, the first aid network supported by ambulances
596 that intervene in the recovery of seriously injured individuals can be unable to access those
597 parts of the urban system most affected by damage to buildings and debris.

598 The debris generation is also included in the ABM layer with the approach already detailed
599 in Section 4.1. Thus, the hybrid characteristics of *Ideal City* allow both the estimation of
600 buildings' damage and debris' generation and the analysis of their cascading effects. In detail,
601 individuals could be killed, injured, or trapped inside damaged buildings or *Ideal City* portions.
602 Moreover, the transportation network can be interrupted blocking the ambulances' intervention
603 and affecting the escape routes for evacuees.

604 **8. APPLICATION**

605 The objective of this work is the development of an integrated platform to assess seismic
606 resilience at the community level for large-scale areas. Five layers have been considered to
607 model community infrastructures, while different physical methods have been implemented to
608 evaluate the infrastructures' vulnerability and their mutual interdependencies. The flowchart

609 depicted in Figure 12 provides a detailed description of the methods and processes used in the
 610 platform.



611

612

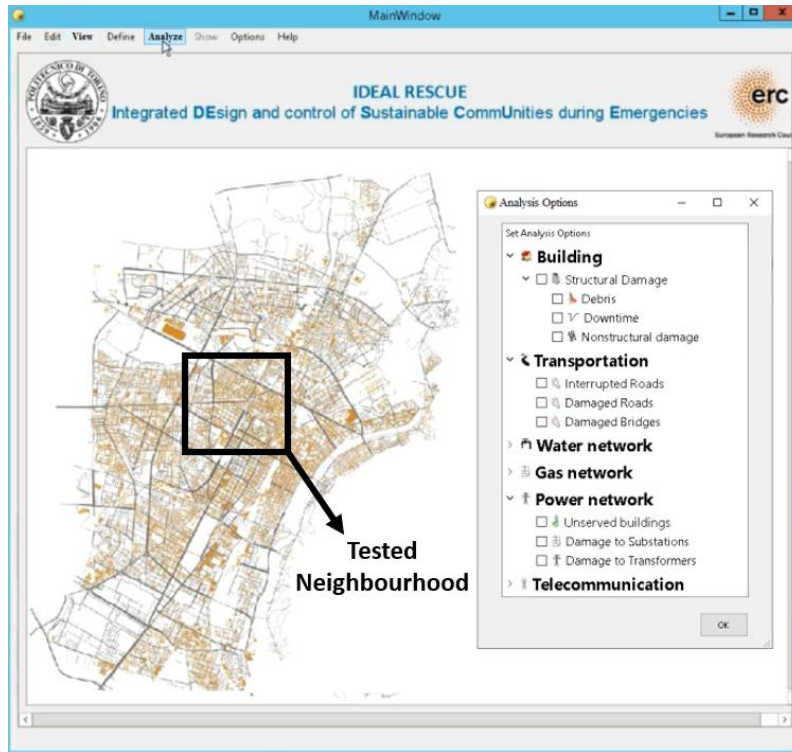
Figure 12. Flowchart of the integrated platform.

613 All the inherent data of the infrastructures are stored in the exposure database. Building stock
 614 represents the main physical layer whose vulnerability is assessed by using a *surrogate* model
 615 based on certain damage states and seismic scenario. The platform allows users to upload
 616 exposure database, while selecting the damage states and the related Engineering Demand
 617 Parameters. Ghobarah (2004) damage states and related maximum inter-story drift thresholds
 618 are set by default in the integrated platform. The user can also define the seismic scenario by
 619 selecting (i) epicenter location, (ii) magnitude of the earthquake, (iii) time-history recorded at
 620 the epicenter, and (iv) ground motion prediction equation to evaluate the geometrical
 621 attenuation at any building location. Ambraseys et al. (1996) attenuation model is set by default

622 while seismic record processing is performed by the embedded OpenSignal tool (Cimellaro &
623 Marasco, 2015).

624 The simulated damage experienced by the buildings is the starting point for taking into
625 account the cascading effects on the RTN, PG, and WDN. Interdependency between buildings
626 and roads is accounted through an RF algorithm which provides the functionality state of each
627 roadway element. Furthermore, the Density Design Method is applied to PG by setting off the
628 transformers located within irreversibly damaged buildings. Based on the buildings' damage
629 and PG's unfunctionality, the Water Network tool for resilience is employed to evaluate the
630 effects on the WDN. Under these conditions, the emergency evacuation is simulated through
631 an Agent-Based model after fixing the common rules adopted by the agents.

632 An application of the developed platform to *Ideal City* hybrid model is herein presented. The
633 virtual city consists of 23420 residential buildings and covers an overall area of 120 km² with
634 a population of 908.129 inhabitants. The building stock of the city is mainly composed of RC
635 buildings (63%) and masonry structures for the remaining parts (37%). Figure 13 illustrates a
636 screenshot of the software's graphical user interface and the related analysis options.



637

638 **Figure 13.** View of *Ideal City* within the software's main window and the dataflow for a
 639 disaster simulation.

640 Different seismic scenarios have been adopted by defining the epicenter location, the moment
 641 magnitude, and the time history recorded at the epicenter. Geometrical attenuation at any
 642 building location has been estimated based on Ambrases' attenuation Ground Motion
 643 Prediction Equation (GMPE) (Ambraseys et al., 1996).

644 Four benchmark horizontal acceleration time histories have been selected using Opensignal
 645 software (Cimellaro & Marasco, 2015). Northridge (Imar County Hospital parking lot in
 646 Sylmar, California) and Kobe (Kobe Japanese Meteorological Agency station, Japan) records
 647 have been assumed to simulate the effects of near-field earthquakes. On the other hand, El
 648 Centro (Imperial Valley Irrigation District substation, California) and Hachinohe (Hachinohe

649 City, Japan) records have been considered as far-field seismic benchmark scenarios. Table 3
 650 lists the main seismological characteristics of each selected record.

651 Table 3. Characteristics of the four selected benchmark time histories.

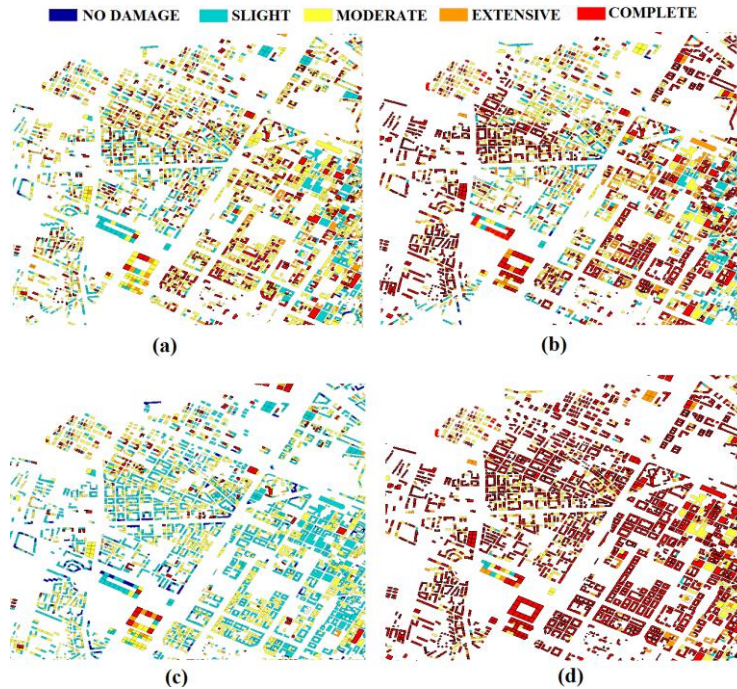
	El Centro	Kobe	Hachinohe	Northridge
Date	5/18/1940	1/17/1995	5/16/1968	1/17/1994
Event	Imperial Valley	Hyogoken Nanbu	Tokachi-oki	California
M _w	6.9	6.8	8.2	6.7
Depth [km]	16.00	17.60	26.00	11.30
PGA [g]	0.35	0.82	0.23	0.84

652

653 The developed platform can provide damage information associated with all the layers of the
 654 analyzed area. Furthermore, the dataflow can be completely managed by the user who can
 655 choose among different options (Figure 13). Analysis flow starts with the damage assessment
 656 on the building portfolio. Once a seismic scenario is defined, a pair of horizontal orthogonal
 657 acceleration time histories have been applied at each building location by considering the
 658 geometrical attenuation.

659 Figure 14 depicts the Damage States (DSs) map of the selected district under different
 660 seismic scenarios. Table 4 lists the percentage of building DSs: Northridge and Kobe scenarios
 661 mainly have caused almost complete damage (about 86% and 79% of buildings, respectively).
 662 Only a few buildings have been found functional (around 1% ranging between undamaged and
 663 slightly damaged for both scenarios). Besides, 40% of moderate damage and 27% of complete
 664 damage has been experienced by the El Centro earthquake, while extensive and slight damage

665 corresponds to 14% and 19%, respectively. Hachinohe earthquake is the less disruptive
 666 scenario where most of the buildings remain functional, 52% of buildings are either undamaged
 667 or slightly damaged, 37% are moderately damaged, while only 9% collapse.



668
 669 **Figure 14.** Building DS maps of *Ideal City* district for (a) El Centro, (b) Kobe, (c)
 670 Hachinohe, and (d) Northridge earthquake scenarios.

671 Table 4. Percentage of buildings DSs for each scenario.

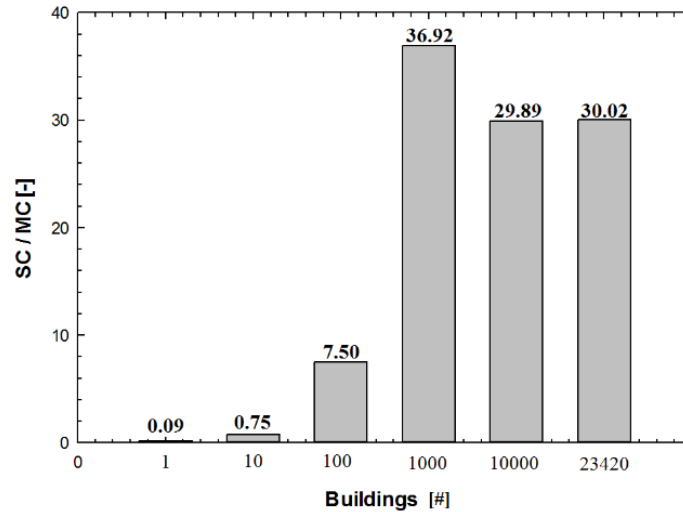
Damage States [%]	El Centro	Kobe	Hachinohe	Northridge
No damage	0.62	0.03	5.9	0.03
Slight	18.75	0.77	45.68	0.77
Moderate	39.38	9.53	36.73	7.17
Extensive	14.1	10.21	2.22	5.83

Complete	27.14	79.47	9.47	86.19
----------	-------	-------	------	-------

672

673 The possibility to use parallel computing to run this demanding computational analysis has
674 been investigated. First, Single Core (SC) and Multi-Core (MC) processing have been
675 compared in terms of elapsed time under different building cluster sizes. Figure 15 illustrates
676 the variability of the mean elapsed time ratio (speedup ratio) vs the number of buildings
677 involved during the analysis.

678 According to the numerical results, SC application is faster when the number of buildings is
679 lower than 10. This is because MC frameworks require more time for spawning processes,
680 assigning tasks, collecting data, and closing processes. Once the processes are spawned, they
681 can be used without closing processes. In the selected case study, the speedup ratio of MC
682 reaches the maximum efficiency when 1000 buildings are analyzed simultaneously. Under this
683 condition, MC is 36 times faster than SC. When the top performance is reached, then an
684 increase of the elapsed time is observed due to the thermal throttling caused by the CPU
685 overheating. Under this condition, the new speedup ratio is about 30 times faster than SC and
686 remains almost constant until the end of the analysis.



687

688

Figure 15. Speedup ratio between Single-Core (SC) and Multiprocessing (MC)

689

computational process.

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702

Once the building damage has been estimated, then different types of interdependencies have been investigated. First, the extension of debris caused by the building damage is evaluated using a machine learning algorithm and the corresponding obstructed roads are identified. Figure 16 illustrates the interrupted roads (red lines) caused by the four selected seismic scenarios for the considered district. Indeed, the Northridge earthquake has caused the largest number of blocked roads (30.48%) followed by Kobe (21.29%) and El Centro (14.49%), while Hachinohe is the less disruptive seismic event with only 4.47% of unfunctional roads.

The blocked roads are not equally distributed over the city. Indeed, some districts are completely isolated due to the amount of debris produced, highlighting the importance of this type of analysis to plan efficient evacuation and rescue operations. The *average vertex degree* and *global efficiency* have been calculated and normalized with respect to the undamaged conditions. Results are shown in Figure 17 where it is possible to see the two indices reducing with the increment of the earthquake severity.

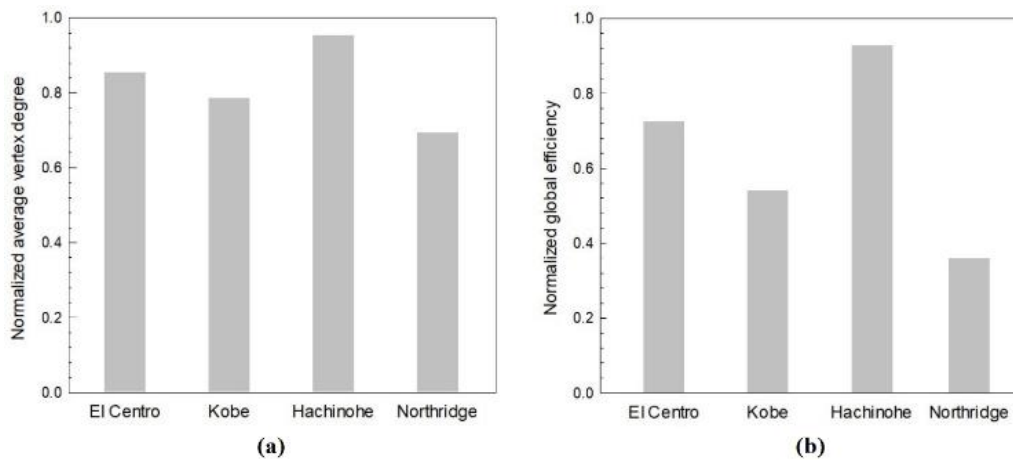


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704

705

Figure 16. Visualization of interrupted roads for (a) El Centro, (b) Kobe, (c) Hachinohe, and (d) Northridge earthquake scenarios.



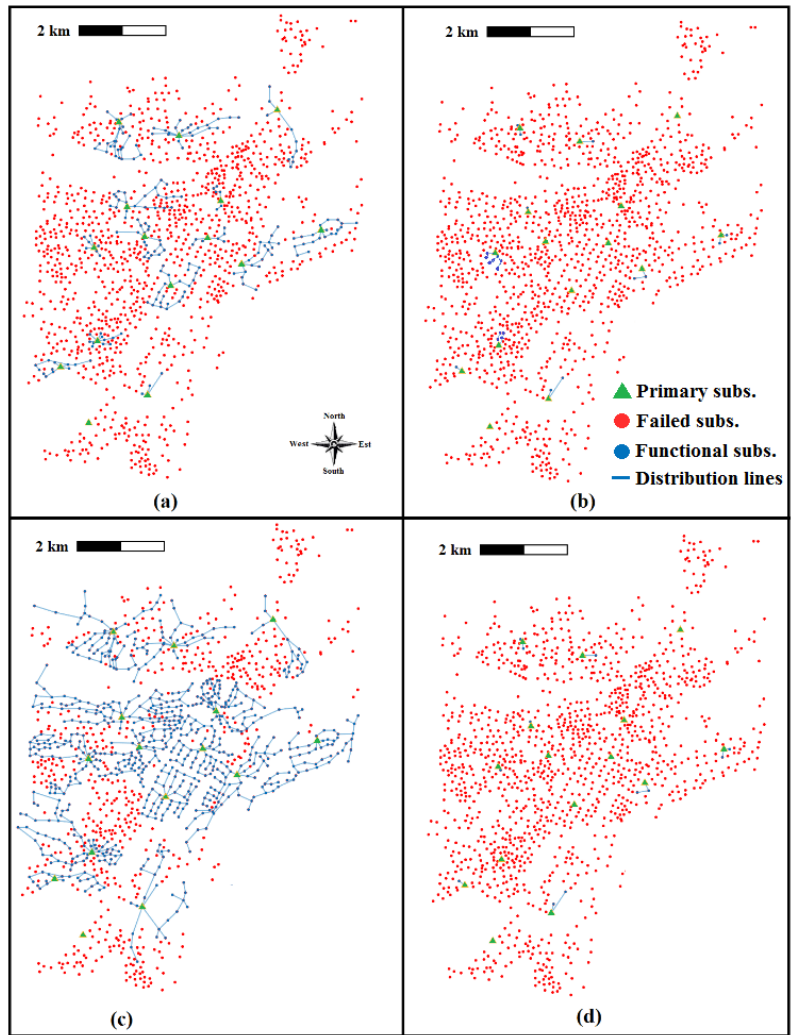
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708

Figure 17. Variation of the normalized average vertex degree (a) and normalized global efficiency (b) under different seismic scenarios.

709 The second interdependency that has been considered correlates the power distribution
710 network with the building damage. The failed electrical substations for the four different
711 seismic events are shown in Figure 18.

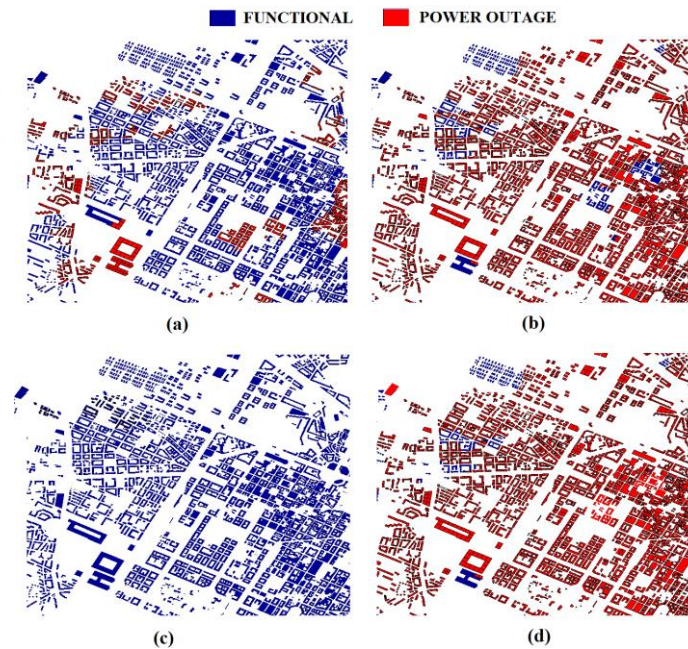


712
713 **Figure 18.** Visualization of PG failure's component for (a) El Centro, (b) Kobe, (c)
714 Hachinohe, and (d) Northridge earthquake scenarios.

715 In detail, the substations that remain functional for Northridge are 12, for Kobe are 25, while
716 for El Centro are 220, and for Hachinohe are 747 out of a total of 1274 substations. These
717 results show that the near-field earthquakes are more disruptive than the far-field earthquakes

718 for the PG. In Figure 19 is shown the impact of the PG's disruption at the building level, where
719 in red are the buildings without power.

720 A simple resilience index (R_{power}) has been introduced as the ratio between the number of
721 users who still have access to electricity and the total population of *Ideal City*. 98.5% of the
722 population is without power after Northridge and Kobe scenarios, while about 80% of the
723 population has no power after the El Centro earthquake. Instead, Hachinohe causes a loss of
724 power for about 40% of users.



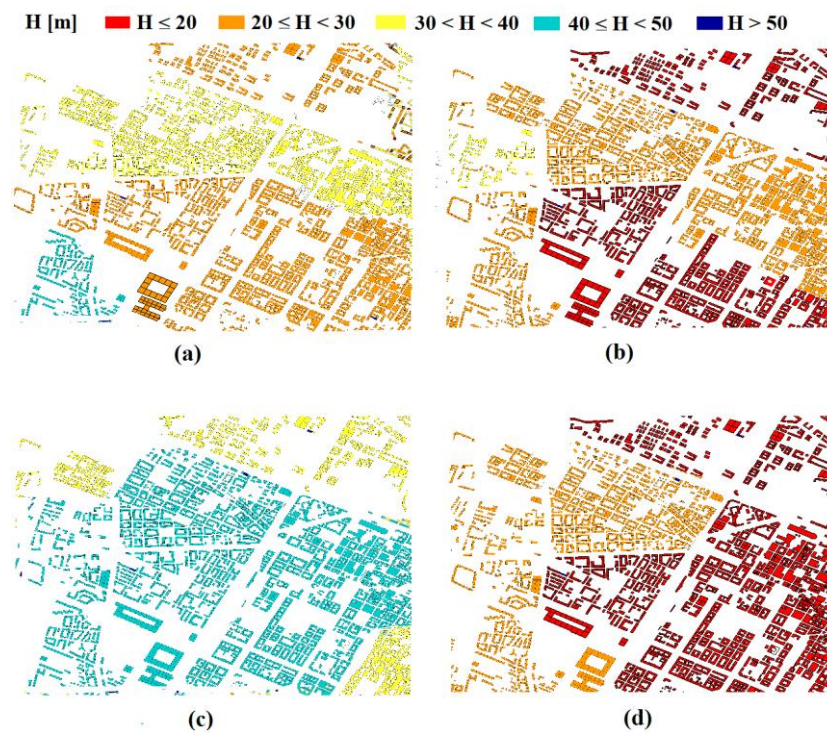
725

726 **Figure 19.** Visualization of buildings with and without electricity for (a) El Centro, (b)

727 Kobe, (c) Hachinohe, and (d) Northridge earthquake scenarios.

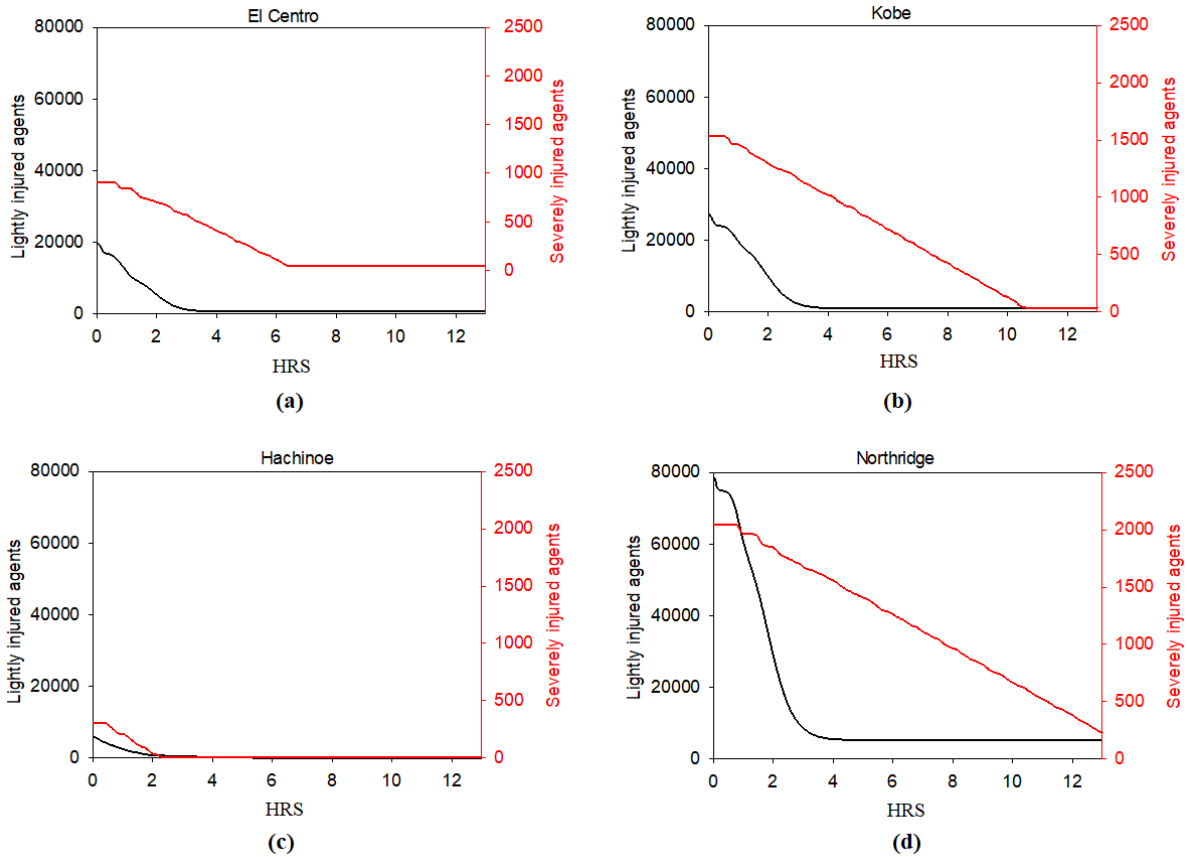
728 Finally, the damage caused by the four benchmark scenarios on the WDN has been
729 investigated. Northridge scenario induced the highest number of damaged pipes while
730 Hachinohe induced the lowest one.

731 Figure 20 depicts the drop in water pressure (m) in each building caused by the damage on
732 the water pipes. The Northridge scenario induced the highest number of damaged pipes while
733 Hachinohe induced the lowest one. The disruption of the pipes is a function of the earthquake
734 characteristics, such as Magnitude, epicenter, depth, etc. Looking at Table 3 in the paper,
735 Northridge earthquake, due to its shallow depth, is a near field earthquake. This makes it more
736 disruptive for the water pipes of the *Ideal city*.



737
738 **Figure 20.** Water pressure distribution after (a) El Centro, (b) Kobe, (c) Hachinohe, and (d)
739 Northridge earthquake scenarios.

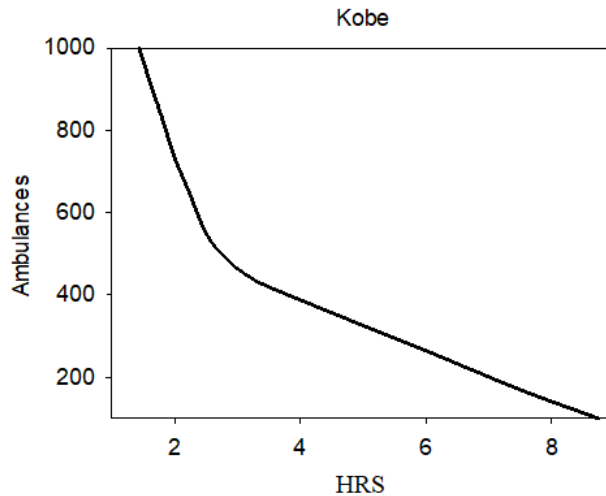
740 Finally, the population response to emergency evacuation has been analyzed by the ABM
741 layer of *Ideal City*. For example, the number of lightly injured individuals walking to hospitals
742 and severely injured individuals that are waiting to be rescued are reported in Figure 21.



743

744 **Figure 21.** Lightly injured agents walking to hospitals and severely injured waiting to be
 745 rescued vs time (hours): (a) El Centro, (b) Kobe, (c) Hachinohe, and (d) Northridge
 746 earthquake scenarios.

747 Furthermore, the platform can also be adopted at the design stage, e.g. to compute the
 748 minimum number of rescue resources (ambulances) to recover the seriously injured
 749 individuals within a fixed period for a certain earthquake scenario (Figure 22).



750

751 **Figure 22.** Kobe event: rescue time (hour of all severely injured individuals as a function
752 of the number of ambulances.

753 The four seismic benchmark scenarios have caused similar effects for all the infrastructures
754 within *Ideal city*. Northridge and Kobe have found to be more disruptive due to the higher
755 PGA. These two near-field seismic scenarios have caused more than 90% of irreversible
756 damage to the building portfolio. Their impact on the RTN have been also devastating, causing
757 a considerable decrease in the normalized global efficiency of the transportation network
758 around 45-55%. A similar trend has been found in the PG, where more than 98% is without
759 power following the Northridge and Kobe earthquakes. Drastically reduction of water pressure
760 has been also accounted for in the WDN after the occurrence of the two aforementioned
761 seismic scenarios. Finally, the number of severely injured agents between 50000 and 60000
762 has been estimated.

763 The Hachinoe scenario has found as the less disruptive scenario for all the networks, while
764 El Centro induced a considerable level of irreversible damage on the analyzed infrastructure.
765 More than 40 % of building stock has experienced irreversible damage following the El Centro

766 scenario, while only 12 % has been found for Hachinoe. These results are also reflected on the
767 RTN, where 75% and 40% of normalized global efficiency have been accounted. 20% and
768 60% of substations have been found functional following El Centro and Hachinoe scenarios,
769 respectively. Finally, Hachinoe has caused only 10000 severely injured agents, while after the
770 occurrence of El Centro scenario, more than 35000 severely injured agents have been found.

771 The large outcomes discrepancies between Hachinoe and El Centro are due to their
772 seismological characteristics. Hachinoe is represented by a greater magnitude and hypocentral
773 depth than El Centro. Therefore, the seismic wave propagation associated with the Hachinoe
774 scenario is more affected by the geometrical attenuation. In fact, the PGA of Hachinoe is about
775 0.23g, while 0.35g is the one of El Centro. In the nonlinear time history analyses, such a kind
776 of discrepancy of PGA will cause considerably different responses.

777 **9. CONCLUDING REMARKS**

778 A computational platform is presented in this paper to analyze the effects of seismic events
779 on an urban community. The platform implements different layers, such as buildings, road
780 transportation networks, power grid, water distribution networks, and socio-technical
781 networks. Specific models have been developed to simulate the interdependency between
782 different layers. The individual seismic response of each building is analyzed through a
783 *surrogate* physical model, including inherent uncertainties. The seismic effects in terms of
784 damage and serviceability for each layer can be computed and visualized. Furthermore, an
785 agent-based model has been developed to simulate the emergency evacuation process and the
786 first-aid operations in post-disaster conditions. Future work is geared towards including gas
787 and telecommunication interdependencies in the analyses.

788 A hybrid model of a virtual city has been used to test the platform under four different seismic
789 scenarios. The main innovative aspects and advantages of the proposed platform are: (i)
790 damage and resilience assessment of critical infrastructures in a large-scale urban environment
791 considering their interdependencies; (ii) graphic visualization of the results obtained by the
792 different layers; (iii) multiprocessing computation; (iv) agent-based modeling for emergency
793 management and evacuation.

794 The platform is intended to support decision-makers and planners to analyze the community
795 response to a seismic event and implement possible countermeasures to improve the overall
796 resilience. The long-term objective is to make individual infrastructures safer, implementing
797 specific actions that allow each network to withstand external perturbations and to mitigate
798 cascading effects due to interdependencies.

799 The current state of the platform does not allow considering the recovery of the damaged
800 structure and infrastructure. This is actually a work in progress that will be included in a future
801 paper. The future work will address both the damage and the restoration analysis of the
802 infrastructure network by incorporation already-developed models within the platform (De
803 Iuliis et al., 2019; Kammouh, Cimellaro, et al., 2018).

804

805

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