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A framework for the assessment of road network resilience: application to a densely populated urban context

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Abstract

Road networks include strategic and critical infrastructures that must operate effectively at any moment for the well-functioning of a country's economy. In this context, the risk of traffic closure and/or limitations is constantly present due to a plurality of natural and man-made hazards. In this work, a novel framework for the assessment of road network resilience to both single and multiple hazards is proposed for applications to large road networks located in densely populated urban/extra-urban areas. Multiple potential sources of hazards and their potential consequences are identified. Strong interaction between the infrastructure and the urban or extra-urban area is considered. Disaster resilience is evaluated by considering both the infrastructure's own assets – such as bridges and viaducts – and the buildings of the urban/extra-urban area where the infrastructure is located. This allows several interdependencies between the road network and buildings to be modelled and considered in the computations, such as the failure of some network connections due to the collapse of some buildings. The main resilience assessment is herein done with respect to earthquake ground motion. Then, some hints are provided for resilience assessment that also accounts for land monitoring data, allowing identification of the optimal connections in post-disaster efficiency assessment of the road network by incorporating information on geohazards from both terrestrial and satellite systems.

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1. Introduction

In recent decades, there has been a significant increase in disaster events resulting from natural hazards (CRED, 2022). Furthermore, the scale of these events' impact has shown exponential growth, affecting both the economy and humanity (Cerè et al., 2017). Projections suggest that by 2050, urban areas will host nearly 70% of the global population, making them vital centres of human settlement and capital accumulation, and consequently, highly susceptible to natural hazard events(Ritchie & Roser, 2018). A global challenge is then to reduce both the direct and indirect impacts on communities facing natural hazards and strengthen their recovery ability (Leichenko, 2011). Thus, as contemporary cities become increasingly vulnerable and exposed to severe hazards, evaluating urban resilience in the aftermath of disasters emerges as a critical concern for the global scientific community. Among the many disaster events threatening nowadays cities, in this paper, we focus on seismic events.

Some of the most used approaches that aim at post-event efficiency assessment are those that model urban infrastructure networks as graphs. In such conceptualizations, these networks serve as physical representations of residential areas, essentially abstracting where people live, i.e., residential buildings. Consequently, these networks work as urban subsystems that require modelling as interdependent networks (Buldyrev et al., 2010; Ukkusuri & Yushimito, 2009). As such, the mutual relationships between these networks are depicted by their overlapping presence within the geographical space they occupy. This results in the identification of a unique complex network that encompasses both the physical components of the city and its inhabitants, termed ‘hybrid social–physical network’ (HSPN) (Bozza et al., 2015; Cavallaro et al., 2014). This approach, grounded in graph theory, facilitates the monitoring of city efficiency through assessing the connectivity of the urban environment. Conversely, the assessment of city efficiency can be viewed as a systemic measure of urban damage under, while simulating its recovery according to a reconstruction strategy (Bozza et al., 2017). Accordingly, our study proposes to evaluate infrastructure damage for an urban area in its entirety, rather than at the level of the single structure, while integrating a performance-based earthquake engineering (PBEE) framework (Deierlein & Moehle, 2004; Krawinkler & Miranda, 2004; Verki & Aval, 2020).

A common framework to integrate probabilistic building performance limit states into the evaluation of community efficiency following earthquakes is indeed based on PBEE. The limit states are delineated according to their impacts on post-earthquake functionality, encompassing categories such as damage triggering inspection, damage leading to loss of functionality, moderate-severe damage, irreparable damage, and collapse. Fragility curves are constructed to establish the relationship between earthquake ground motion intensity and the probability of surpassing each limit state. Additionally, a distinct efficiency index is usually outlined for each limit state. The result is a probabilistic framework for resilience assessment at the building/infrastructure level, for a given ground motion intensity. This kind of assessment has proven very effective in informing planning and policy decisions about earthquake risk.

Along these lines, urban resilience has been defined diversely. Meerow et al. (2016) offer one of the most comprehensive definitions, describing urban resilience as the capacity of an urban system to maintain desired functions despite disturbances. They also emphasize the importance of preserving existing assets, aligning closely with concepts of disaster risk preparedness and response. The complexity of enhancing resilience in urban areas is evident, considering the multitude of components, processes, and interactions across physical, legal, and virtual boundaries (Desouza & Flanery, 2013). International disaster response tends to favor rural areas over urban ones, with limited support for urban reconstruction efforts from humanitarian agencies due to the complexities involved (Daly et al., 2017; MacRae & Hodgkin, n.d.). Urban rebuilding faces significant challenges due to governance layers, community interests, and mixed public-private entities, making coordination and decision-making more complex than in rural settings (Daly et al., 2017). Disaster resilience consists of preparedness, response, recovery, and adaptation actions, although the literature lacks a systematic evaluation of their relationships and implications in urban planning (Rus et al., 2018). This confusion among stakeholders is compounded by uncertainty in investment direction throughout the disaster risk management cycle (Kawasaki & Rhyner, 2018). While urban system resilience is not solely dependent on recovery capability, the recovery process significantly contributes to overall resilience (Meerow et al., 2016).

In this paper, we adhere to the simple paradigm suggesting that the seismic resilience of an urban environment would be enhanced by a high post-event efficiency level, regardless of the various interpretations of resilience mentioned earlier. Put differently, we gauge the resilience of a system by its ability to maintain a certain level of efficiency following a seismic event. To this end, we propose a framework for evaluating the engineering efficiency of a road network (RN) that connects healthcare facilities. This framework proves particularly useful in scenarios where ground emergency medical services (EMS), such as ambulances, are preferred over helicopter EMSs for transportation between nodes of the RN, as is often the case in densely populated urban areas (Chen et al., 2018; Lerner et al., 1999). We create and examine simple relationships to measure efficiency, considering how these could be used in traditional urban disaster management. The uniqueness of our proposed framework lies in its independence from time and its ability to assess various factors influencing RN efficiency. Thus, we consider the pre-event RN performance and the number of post-event road interruptions, while assessing the overall damage caused to buildings and bridges.

2. Methodology

The road network (RN) is modelled as a QGIS-informed graph. QGIS is a software for geographic information systems (GIS) that integrates a wide variety of data and helps to identify specific information by acquiring and georeferencing. The RN is represented by a graph composed of a discrete set of nodes and roads. The built environment encompasses structures such as buildings and bridges whose damage would cause a road disruption. The network is conceptualized as a framework upon which urban services are organized. We use QGIS because it can precisely locate each building and bridge throughout the RN, and establishes their typologies, crucial for the subsequent phase of the proposed framework, namely, the assessment of the seismic vulnerability of the structures. Specifically, bridge typologies are classified based on the main seismic response parameters such as pier type, deck type, and pier-to-deck connection type. Conversely, building typology classifications are limited to only the height of buildings, assuming, for the sake of brevity, that all buildings are made of reinforced concrete (RC) framed structures.

Once the RN is modelled, we simulate earthquake scenarios by comparing hazard analyses with the probabilistic performance of buildings and bridges, in terms of limit states. This approach is different from the use of a ground Motion Prediction Equation (GMPE) and choosing a past seismic event (Miano et al. 2016 and 2020). Specifically, two scenarios – hereinafter labeled *Sc50* and *Sc475* – are considered, corresponding to seismic events with values of return period T_r equal to 50 years and 475 years, respectively. This phase is important for assessing the seismic demand in terms of peak ground acceleration, namely, a PGA_{dem} on the structures within the RN. Thus, every simulation of the earthquake event will entail subjecting all bridges and buildings within the RN to the corresponding PGA_{dem}. Each data point in the graphical representation depicted in Fig. 2 will receive a logic value of 1 if it meets the condition:

$$PGA_{dem} > PGA_{cap} \tag{1}$$

or *0* otherwise. In Eq. (1), the seismic demand and capacity are modelled as follows:

$$PGA_{dem} = \mu_{50}\, exp(\beta A) \tag{2}$$

$$PGA_{cap} = M_{50}\, exp(BA) \tag{3}$$

where A is a uniformly distributed pseudorandom scalar, μ_{50} and M_{50} are the 50th percentile of the lognormal distribution of demand and capacity, respectively, whereas β and B denote their standard deviations. The choice of distributions is guided by appropriateness for the specific case under consideration. In Section 3, we adopt distributions investigated by Moschonas et al. (2009) for bridges, while relying on the study by Rosti et al. (2021) for buildings. Subsequently, after each simulation, roads containing at least one structure marked with a value of *1* will be deemed disrupted, resulting in a decrease in the operational efficiency of the RN, as detailed in the subsequent paragraph.

In the landscape of urbanization, the efficiency of a RN plays a pivotal role in achieving desired levels of resilience and, in a sense, sustainability, for a city. We define efficiency as the measure of how quickly the roads within a specific urban context connect critical nodes, such as hospitals. Thus, in case of a RN consisting of n roads, the efficiency of the i^{th} road in the j^{th} simulation, denoted as E_{ij}, is assessed using the following formula:

$$E_{ij} = 1 - \frac{t_i}{t_{ref}} \tag{4}$$

where i ranges from 1 to n, t_i represents the mean travel time of the i^{th} road, and tref denotes the maximum time required to connect the two critical nodes of interest. In the application of this paper reported in Section 3, we select t_{ref} to be the time t_{ooh}, commonly referred to as out-of-hospital time (Spaite et al., 1993), specifically referring to the patient transport phase. The mean travel time of the i^{th} path within the road network is calculated as follows:

$$t_i = \frac{L_i}{v_i} \tag{5}$$

where L_i represents the path length, and v_i is the mean velocity. The values estimated for L_i and v_i of Eq. (5) are sourced from QGIS. When selecting between ground EMS and helicopter EMS for transportation between two hospitals or from a hospital to any other critical node, hospital managers must decide which route offers optimal intervention for ground EMS (Chen et al., 2018; Lerner et al., 1999). To facilitate this decision-making process, we define t_{ooh} as the maximum travel time t_{max} among i suitable routes, with an additional 50% accounting for uncertainties related to fluctuating traffic conditions and road availability (Spaite et al., 1993). This is expressed as follows:

$$t_{ooh} = 1.5\ t_{max} \tag{6}$$

Since we are conducting a post-recovery assessment, we aim to ascertain how the efficiency of the RN changes in a post-event scenario. Whenever a road is indexed with a 1 digit during a simulation, indicating disruption, its efficiency E_{ij} will be considered null. Therefore, under the j^{th} simulation, the RN efficiency (denoted as E_{RN}) is the maximum efficiency E_j within the RN among the available roads marked with only 0 digits. This allows one to evaluate changes in RN efficiency in response to seismic events.

3. Application to Real Case-Study and Results

The overarching framework outlined above holds potential applicability to a wide array of critical infrastructures within road networks, including hospitals, stadiums, theaters, administrative buildings, and more. This adaptability arises from an efficiency index that accounts for the road travel time. Within this context, we apply our methodology to a case study representing a distinct urban context featuring two prominent hospitals. In the analysis of hospital urban networks, we employ the parameter t_{ooh}, which is commonly referred to as out-of-hospital time (Spaite et al., 1993). More precisely, t_{ooh} denotes a particular segment of the overall out-of-hospital time, representing the duration required by emergency medical service (EMS) personnel to transport the patient from their location to the nearest healthcare facility. The case studies focus on the city of Naples, Italy. It has nearly one million inhabitants, and spans 130.17 km², resulting in a high population density in Naples. Furthermore, this study area comprises a significant number of buildings integrated into the RN. Concerning seismic hazard, the seismic demand PGA_{dem} is derived from the probabilistic seismic hazard analysis conducted by the Italian National Institute for Geophysics and Volcanoloty (Stucchi et al., 2011), which gives expected PGA values for various return periods across entire Italy. The PGA capacity PGA_{cap} of the structures, instead, is evaluated by adopting fragility curves documented in Moschonas et al. (2009) for bridges and Rosti et al. 2021) for buildings. This process enables the determination of the damage state (DS) incurred by each structure. In this context, it is important to meticulously define the practical implications of each DS, as exceeding a certain DS threshold could lead to the road's interruption. Specifically, regarding bridges, Moschonas et al. (2009) have established four DSs in addition to the no-damage state (DS0), namely: minor/slight (DS1), moderate (DS2), major/extensive (DS3), and failure/collapse (DS4). To comprehensively interpret these DSs, Moschonas et al. drew upon various studies including those by Choi et al. (2004), Erduran & Yakut (2004), and Basöz et al. (1999). Concerning RC buildings, Rosti et al. (2021) defined five DSs in accordance with the EMS-98 classification (Grünthal & European Seismological Commission. Working Group "Macroseismic Scales," 1998). These DSs correspond to the following levels of damage for vertical structures: no damage (DS0), insignificant to negligible (DS1), considerable to serious (DS2), very serious (DS3), partially collapsed (DS4), and collapsed (DS5). We have fixed that reaching a *PGA* capacity corresponding to an intermediate DS between DS1 and DS2 is adequate to trigger road interruption in the case of Scenario *Sc50* with a return period T_r = 50 y. Conversely, reaching DS3 would lead to road interruption in the case of Scenario *Sc475* with return period T_r = 475 y. Part of the city of Naples, in southern Italy, is identified via QGIS and depicted in Fig. 1(a). The hilly area of Naples ("Area collinare di Napoli" in Italian), as depicted in Fig. 1(b), is a densely populated region known for its historic significance, cultural richness, and bustling atmosphere. It is mostly dominated by residential neighborhoods and is home to a significant portion of the city's population. Moreover, this area is host to critical healthcare facilities, such as the two critical nodes of this study, i.e., Cardarelli Hospital and San Gennaro Hospital, which are respectively depicted in Fig. 1(c) and 1(d).

Fig. 1. (a) Satellite image of a part of the city of Naples, Italy, sourced from Google Maps, and (b) hilly area of Naples, in a close-up view integrated with QGIS, with the five paths forming the relevant RN. The red stars indicate the locations of the two hospitals, i.e., (c) Cardarelli Hospital and (d) San Gennaro Hospital.

The seismic exposure of the area depicted in Fig. 1(b) is characterized by the following features. The green, blue, and orange paths are located across both the urban area and segments of an urban highway infrastructure named

Tangenziale di Napoli (Ta.Na.). Such paths contain respectively: 6 bridges and 90 buildings; 3 bridges and 199 buildings; and 6 bridges and 74 buildings. Conversely, the pink and yellow paths solely traverse urban areas and contain, respectively: 1 bridge and 154 buildings; and 280 buildings and no bridges. The seismic capacities of bridges and buildings involved in these paths are expressed in terms of median and standard deviation parameters for each relevant fragility curve sourced from the literature (Moschonas et al., 2009; Rosti et al., 2021). The proposed framework is implemented for the RN relevant to the city of Naples through the methodology described in Section 2. Specifically, after N_{sim} simulations of the seismic event, we assess the post-event efficiency through Eq. (4). Then, since a certain degree of uncertainty is considered in this study due to Eqs. (2) and (3), we want to estimate after how many simulations the value of efficiency is stable. To do that, we calculate the mean value and standard deviation of the assessed efficiency index as follows:

$$E_m = \frac{\sum_{j=1}^{N_{sim}} E_j}{N_{sim}} \tag{7}$$

$$E_{std} = \left[\frac{\sum_{j=1}^{N_{sim}} (E_j - E_m)^2}{N_{sim}}\right]^{1/2} \tag{8}$$

where E_j is the maximum post-event efficiency among the roads that are still available, as indicated in Section 2.3, and N_{sim} is the number of simulations. The values of Eqs. (7) and (8) for the Scenario *Sc475* are depicted in Fig. 2.

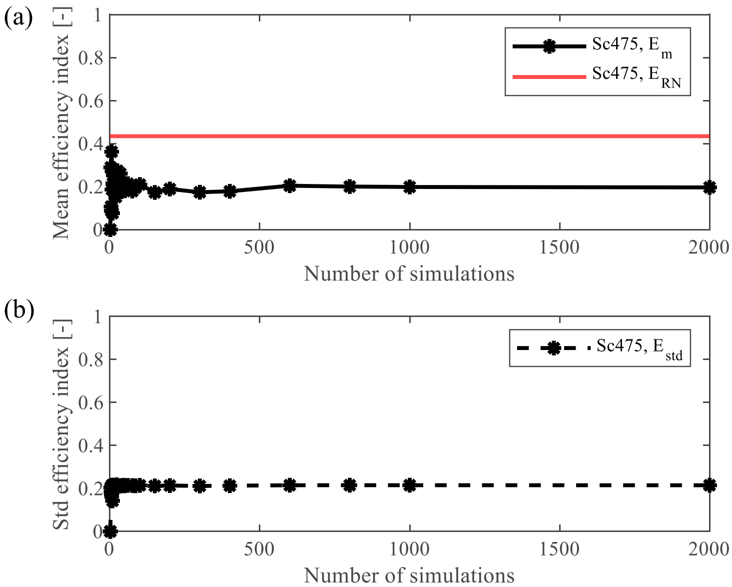

Fig. 2. Efficiency of the investigated road network (RN) according to the definition of Eq. (4) and (7), for a seismic scenario with Tr = 475 years.

The mean value of the efficiency index stabilizes after about 1000 simulations at approximately E_m = 0.2. In the pre-event stage, the maximum value of the RN efficiency E_{RN} is higher than 0.4. This means that, according to our model, a seismic scenario with return period T_r = 475 y would cause a RN efficiency drop of approximately 50%. With regard to scenario *Sc50,* which corresponds to T_r = 50 y, the values from Eqs. (7) and (8) are illustrated in Fig. 3. The mean efficiency index stabilizes around E_m = 0.37 after approximately 1000 simulations. The maximum RN efficiency prior to the seismic event, E_{RN}, exceeds 0.4. This indicates that, as per our model simulating a seismic scenario with return period T_r = 50 y, the RN efficiency results in approximately an 8% reduction.

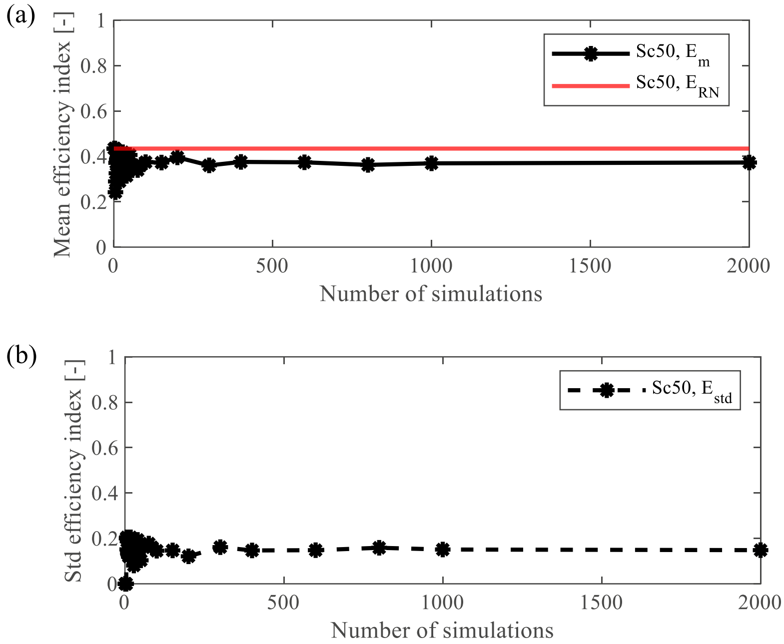

Fig. 3. Efficiency of the analysed road network (RN) in response to a seismic scenario with a return period of *Tr* = 50 years.

4. Conclusions

This study introduced a novel framework to assess the resilience of urban road networks facing earthquake hazard, both directly (through damage to road infrastructures) and indirectly (through earthquake-induced tipping of buildings lying on the side of the road network). The proposed method has been tested on one application to a large road network in a densely populated urban area in Naples, Italy.

The results of this application show how a seismic scenario with 50-years return period will return an 8% reduction in the maximum efficiency of the road network (with respect to pre-earthquake conditions). Under a more severe event with 475-years return period (corresponding to life safety performance objective in design and assessment of engineering structures), this efficiency drop can reach as far as 50%.

These values clearly indicate that the seismic risk should not only be considered, as it is more commonly done, only at the level of the single structure or infrastructure. Disruptions to the whole city transport system can only be addressed with a network level analysis, as done here. These are non-negligible, considering the potential need of hospital-to-hospital transportation following a major earthquake; in particular in the Naples city area, where seismic hazard is medium-high.

Future works will expand on the preliminary results reported here, considering extensions of the proposed methodology to other applications, such as rural roads connecting major urban centers in hillside areas, as well as other potential natural hazards.

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