Definition of an enriched GIS network for evacuation planning

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Abstract: Among the most serious natural disasters, earthquakes cause severe damages to infrastructures and building, can kill or injure thousands of humans and animals and, in the luckiest circumstances, just make people homeless destroying communities, habitats, economies and mental equilibrium. In order to minimise the loss of lives, an effective evacuation plan to cope with worldwide disasters is required. In this paper we describe a novel approach to timely formulate an evacuation plan of an area struck by an earthquake. The proposed solution leverages on a two-steps modeling framework: *i*) a method that extracts from enriched GIS data a network description of the area to be evacuated; *ii*) a dynamic optimization model that calculates the safest paths citizens should follow to reach pre-identified safe areas. While the network is computed off-line at design time, the optimization model, or one of its reductions, can be embedded in a real-time system that, recomputing it several times, can guide citizen after a natural disaster even in case of high dynamic scenario. Our approach is demonstrated on a real study case: the medieval center of the Italian town of Sulmona, for which detailed GIS data with information on the urban structure and building vulnerability are available.

1 INTRODUCTION

Every day, natural disasters all around the world fill the reports of newspapers, radio, tv and other media. Supranational organisations typically define disaster according to their line of work. For the World Health Organization (WHO), a disaster is an occurrence disrupting the normal conditions of existence and causing a level of suffering that exceeds the capacity of adjustment of the affected community (W.H.O., 1999). According to the United Nations Internationals Strategy for Disaster Reduction (UN-ISDR), a disaster is "a serious disruption in the functioning of the community or a society causing wide spread material, economical, social and environmental losses that exceed the ability of affected society to cope using its own resources (Mahar et al., 2013)." Gunns (Gunn, 2003) focuses more on causes than on consequences, and defines a disaster as the result of a vast ecological breakdown in the relations between man and environment. Three conditions should occur in an event to render it a disaster: it must disrupt the normal conditions of life, exceed the local capacity of recovery, and affect a relevant amount of people (without people, there would be no disaster but just a physical phenomenon (W.H.O., 1999)).

Every year, more than 500 disasters are estimated to strike our planet, killing around 75,000 people and impacting more than 200 million others (Van Wassenhove, 2006). Among recent disasters, either natural (earthquakes, volcanic eruptions, landslides, floods, tsunamis, hurricanes, typhoons) or provoked by man (terrorist attacks, chemical or nuclear leakages etc.), the most remarkable losses were recorded in: the earthquakes of Nepal (April 2015), Japan (March 2011), Haiti (January 2010), Chichi (Taiwan, September 1999), Bam (Iran, December 2003), Kashmir (Pakistan, October 2005), and Chile (May 1960); various tsunamis in Japan and the Indian Ocean; the major hurricanes Katrina, Rita, and Sandy in the US; and the 9/11 attacks in US (Pyakurel et al., 2019).

Relatively limited in space, yet mostly concentrated on an urban area, the 2009 L'Aquila earthquake

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(Italy) unveiled unprecedented challenges for logistics planners. The earthquake caused vast damages to the town and to its infrastructures, which crumbled, and existing emergency response systems were destroyed. This resulted in a very grim situation: besides 309 casualties (Alexander, 2010), approximately 1,500 people were injured and over 65,000 lose their homes (Hooper, 2009).

The persisting threat of disasters of this type results in a massive safety demand that, however, unfortunately exceeds the resources available to make houses and infrastructures intrinsically safe: therefore, effective emergency plans to cope with disasters will continue to be a need worldwide. Systematic plans of emergency logistics are however very often neglected. The Fritz Institute (F.I., 2005) reported that logistics planning during the 2004 Indian Ocean tsunami was conducted with no computer support and without the presence of logistics experts. Instead, most impacts of catastrophes can be mitigated by planning in advance and adopting specific measures of disaster management (Alexander, 2002).

The use of a GIS system is very often related to the analysis of transport networks. To do this there are specific GIS systems called GIS-T that require new data structures to represent the complexities of transportation networks. Manfred M. Fischer shows in his book (Fischer, 2006) how to identify several improvements of the traditional network data model that are needed to support advanced network analysis in a ground transportation context. Deelesh Mandloi et al. (Mandloi and Thill, 2010) presented an object-oriented data model to represent the multi-modal, indoor/outdoor transportation network of an urban area that can be used for route planning and navigation and to perform other network analyses.

In this paper, we describe our first attempt to develop an emergency evacuation plan for potential disaster (earthquake) sites. After a small digression on disaster management (Section 2), it starts with the development of methods to extract from an enriched GIS data a detailed network (graph) description together with attributes of the area to be evacuated. Safe places are then determined using already existing assorted tools and technologies (Section 3). Then, we formulate a dynamic optimization model which seeks to pick pre-identified safe areas from the already available locations and prescribe traffic flow plans so as to minimize total evacuation time and casualties (Section 4). Finally, we apply the overall methodology to the study case of the Italian city of Sulmona (Section 5). Brief conclusions end the paper (Section 6).

2 DISASTER MANAGEMENT

Disaster Management (DM) aims at reducing, or possibly avoiding, potential losses from hazards, and at assuring prompt and appropriate assistance to the victims. According to Mansourian (Mansourian, 2005), DM can be undertaken by operations that include *preparedness*, *response*, *recovery*, and *mitigation* as shown in Figure 1. *Preparedness* encompasses all the planning activities performed by various Government organizations, NGO's, businesses and other national and international organizations to quickly respond to disaster, in anticipation of its occurrence. *Response* refers to the immediate activities and efforts which seek to address the immediate and short term effects of disaster, focusing primarily on the actions necessary to save lives and protect properties, e.g.: efforts to minimize hazards induced by the disaster, rescue and relief operations, fire fighting, medical aids, shelters, evacuation, law enforcement and security. *Recovery* indicates all those activities (like reconstruction of buildings, exemption in taxes and long term medical care/counseling) which brings back the community to its normal condition. Along with prevention, *mitigation* requires all those activities that minimize the effects of the disaster, for example building codes and zoning, vulnerability analysis and public education (Kumar et al., 2013).

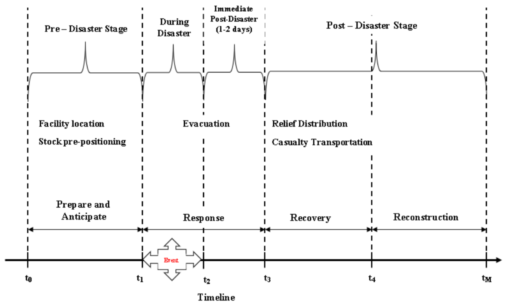

Figure 1: Timeline for the various operations performed before and after disasters.

Anhorn and Khazai (Anhorn and Khazai, 2015) introduced a methodology to rank suitability of open spaces for contingency planning and placement of shelter in the immediate aftermath of a disaster. Using a combination of two factors for the ope space suitability index. The *Disaster Management* illustrates the ongoing process by which governments, businesses actors and civil society prepare plans to reduce disaster impact, react during and immediately following a disaster, and take steps to recover after a disaster has occurred. A complete Disaster Management cycle includes public policies reshaping and plan design that either act on the causes of disasters or mitigate their effects on people, property, and infrastructure.

Unpredictability and the uncertain nature of disasters are the key challenges of designing emergency evacuation plans. Evacuation can be mandatory, recommended or voluntary; besides, it may differ by scale, objects of relocation, and levels of control by the authorities. Evacuation plan is very essential and very necessary for those areas which are highly vulnerable and susceptible to disasters. An emergency evacuation plan assigns evacuees to fixed routes and directions before the disaster, and defines evacuation policies for the occupants of areas subject to the risk of a disaster (Campos et al., 2012). Disaster operations can be performed before or after disaster occurrence, and emergency logistics consists of the process of planning, managing, and controlling the flow of resources to provide relief to the people affected. Its planning presents key challenges that do not normally occur in ordinary business logistics (Sheu, 2007). Kovács, Spens et. al (Kovács and Spens, 2007), stress that the importance of logistics is quite underestimated in pre- and post-disaster operation, being the relevant organizations typically more concerned with fundraising. Still, a large number of researches addressed those challenges via statistical or probabilistic models (Coles and Pericchi, 2003; Xu et al., 2010), queuing theory (Artalejo, 2000), simulation (Hu et al., 2008; Reshetin and Regens, 2003), decision theory (Cret et al., 1993; Tamura et al., 2000), fuzzy methods (Esogbue et al., 1992; Jiang et al., 2009), and most commonly, optimization models and algorithms.

GIS applications in disaster management are progressively transforming into a very useful tool that helps in the processing of related emergency activities and in reducing extremely critical times in emergency management operations (Abdalla, 2016; Müller et al., 2010).

3 NETWORK DEFINITION

In this section, we discuss how to define a city network from GIS data specifically tailored for the definition of evacuation plans for pedestrians in case of an earthquake. We stress that, in order to define a good evacuation plan, it is not enough to consider shortest routes: besides distance, it is in fact necessary to take into account such factors as the intrinsic risk of buildings, street/road capacities, the numerical amount of people who need evacuation in each specific zone, and time. For example, shortest paths might include high-risk streets, or streets directly affected by the disaster that should be excluded from the evacuation plan. But even if the path does not touch risky zones, should everyone concentrate into it, the streets would become overcrowded and form a bottleneck that impedes evacuation. Thus, the network is enriched with a rich complex of information to be used in order to find an appropriate trade-off between total evacuation time and people safety.

We build the network in two phases: the first concerns on collecting information about the city, the second regards the transformation of data into nodes, edges and attributes of a graph. To obtain a reusable model, an object-oriented design is used: this involves the creation of the *City* class which uses the *Building*, *Crossroad*, *Waiting Area*, *Census Area* and *Street* classes, each dedicated to represent a specific information. Then, a *CityGraph* class is used to obtain the desired network.

3.1 Data Collection

The purpose of the first phase is to collect all the city (or area) data that are relevant for the present study. As this information has a prevalent geographical nature, spatial data are mainly used. Among the different methods of representing spatial data, with no loss of generality we adopt the terminology of the *shapefile* format, which includes primitive geometric elements, such as points, polylines and polygons (called *features*), flanked by textual information (called *attributes*).

Beyond the basic geometric information on buildings, crossroads and streets we also need to consider the information necessary for evacuation planning; here is a list:

- risk of buildings: integer, indicates the level of risk from the most seismically vulnerable to the most resilient (there exist several scales expressing seismic risks);
- people in buildings: number obtained from the city census;
- streets length and width: in meters, useful to understand how many people a street can contain at a given moment in time;
- risk of streets: initially estimated as the highest degree of risk of the buildings flanking the street, but the estimate can be refined as a function of width, length, and of more information on the street (such as the presence of dangerous artifacts or peculiarities of any kind);
- waiting areas: obtained from data provided by the Civil Protection Services, in particular related to geometry and capacity of sheltering people.

The above information are saved as attributes of the previously mentioned classes. In detail, the class *City* includes the lists of buildings, crossroads, waiting areas, census areas, and streets. Additionally, the class *City* needs to specify the Spatial Reference System (SRS) used for spatial data and the functions to load data from shapefiles.

Attributes of the class *Building* are the ID, the building footprint geometry, the coordinates of its position in the street, the risk factor, and the number of people who are assumed to live there. Two types of geometric representations are used for buildings: in one the building footprint is represented as a polygon (necessary to infer, e.g., the area and the number of people occupying the building); in the other, buildings are represented as points to indicate the position in the street. This second representation, indicating the building access points, is necessary to associate buildings with the street network, a relation not always explicitly available from data sets. Therefore, a method must be devised to infer the point representation from the polygonal representation. Given the shapefiles of streets and buildings, a basic method is to calculate the shortest distance between the building and the streets that surround it, and then determine the point on the street network that represents the access to the building. More sophisticated methods can be devised if more precise information is available, such as building street numbers.

The class *Crossroad* contains the crossroad ID and geometric position. The class *Street* the street ID, the position of its endpoints (which must match with crossroads), the linear geometry, the average width, the length, the risk factor, and a list of the associated buildings and waiting areas. The class *WaitingArea* includes the ID, the geometry, the position and the area capacity in terms of people. Finally, the class *CensusArea* includes the area ID, its geometry, the buildings it contains and the total amount of residents included. Unlike the other classes, this one will not be used to create the graph, but only to estimate the number of residents in each building.

Figure 2: Screenshot of the area from Google Earth.

Figure 3: Screenshot of shapefiles in the area.

To better understand the typical GIS data which provide data to the above classes, an example may be of help. Figure 2 shows a screenshot satellite picture taken from Google Earth, Figure 3 displays the corresponding shapefiles with buildings (violet areas), streets (yellow lines), crossroads (red points), and position of buildings inside the network (orange points).

3.2 Transformation into a Graph

Once we have all the information about a city, it is possible to create a graph representing the city as a network.

To make graph usage more efficient, we adopt a hierarchical approach and define in fact two graphs: one more detailed, and another more generic. Both graphs are undirected, since we can assume pedestrians move in both street directions. In the first graph $G_D = (V, E)$, the set of nodes V is the union of the following subsets:

- V_B (Buildings). With attributes:
  - *building type*: private, public (church, town hall, school, library, ...) or strategic (used by Civil Protection)
  - *position*: latitude and longitude coordinates
  - *risk*: integer number indicating the building seismic vulnerability, the higher the more risky
  - *number of people*: estimation of the amount of people that could be in a building at a particular time.
- V_C (Crossroads). With the only attribute *position*, expressed by latitude and longitude.
- V_{WA} (Waiting Areas). With attributes *position* and *capacity*, that is the number of people that the area can contain.

For the construction of the edges it is useful to define the concept of *point of interest* as any possible starting or ending point in a route. These points are all those nodes of the graph that do not represent crossroads ($V \setminus V_C$); for the moment they coincide with buildings and waiting areas, but in future developments their set can be augmented.

Now we can define the set of edges E, obtained as the union of the following sets:

- E_S (Streets). The elements connecting a crossroad to another (corresponding to the roads described in the shapefile of the available GIS data). Attributes: *width* and *length* expressed in meters, *buildings* as a list of the buildings facing the street, and *risk* as the largest degree of risk of a building in the latter list.

- E_{HS} (Half-Streets). Parts of streets that connect points of interests to each other or to a crossroad. To divide a street into half-streets, we implemented a function called *divideStreetWithPointsOfInterest()* that proceeds through the street starting from an endpoint. When a point of interest is found, a new edge that connects it to the crossroad is saved. The function then restarts from the last point of interest found, search for the next, and so on until it reaches the second endpoint. Attributes inherit those of the associated edge (street) but with updated length, except those related to the points of interest.

Figures 4 and 5 show the graph representation of the data collected on the area exemplified in Figures 2 and 3. In the former one can see red nodes (crossroads), blue nodes (buildings) and the edges that connect them to each other. The latter figure shows the more generic graph involving only crossroad nodes.

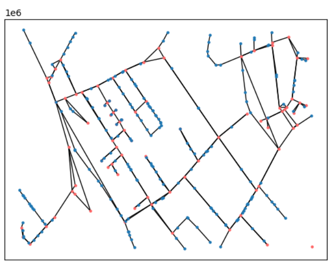

Figure 4: Area represented by the complete graph.

As said, this procedure generates the detailed graph $G_D = (V, E)$, where $V = (V_B \cup V_C \cup V_{WA})$ and $E = (E_S \cup E_{HS})$, containing the whole information necessary for the evacuation plan. A more abstract graph $G_A = (V_C, E_S)$ is then obtained by finding the subgraph induced in G_D by the crossroad nodes V_C.

Obviously, the detailed graph contains many more nodes than the abstract graph: computing a path from a point of interest to another in G_D can however be

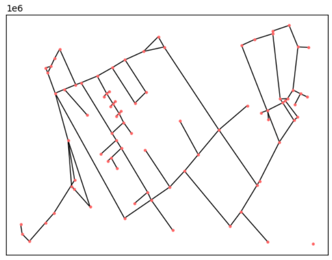

Figure 5: Area represented by the crossroads graph.

fastened by exploiting G_A. To find a route between two points of interest we can distinguish three steps: departure, search and arrival. In the departure step, the detailed graph is explored in order to move from the starting point of interest (the origin) to the nearest crossroad that brings closer to the destination. In the search step, the algorithm uses G_A to find a route from the crossroad found in the departure step to a crossroad that is as close as possible to the destination (i.e., one of the endpoints of the street that contains it). Finally, in the arrival step one moves from a crossroads to the destination, so it is again necessary to use G_D. Using this method, the CPU time of the routines used in the elaboration of the evacuation plan can be substantially reduced.

4 GENERATING THE EVACUATION PLAN

To dynamically generate a plan that minimizes the total evacuation time we adapted a linear optimization model originally developed by (Arbib et al., 2019) for building evacuation. The model had to be customized with respect to several parameters, and rescaled to the network of several orders of magnitude. The large scale required forced us to consider, for a first approach, various simplifications and only a limited amount of the information supplied by the network. Although some work should then be devoted to extend the model, the results obtained are however encouraging in terms of the approach viability. A high-level description of the model is given in the next section 4.1, and parameter customization is reported in section 4.2.

4.1 The Optimization Model

Based on earlier work of (Choi et al., 1988), (Arbib et al., 2019) devised a discrete-time network stock-and-flow model where one finds, at increasing time stamps τ, the maximum amount of people that can be evacuated within τ to a given set of safe areas. The starting point of the model is a static oriented network $G = (N,A)$ obtained from the graph G_D of section 3.2 by a suitable embedding of the city streets into a set N of elementary cells; the arcs in A connect geometrically adjacent cells in both directions. Cells may in general have different shapes or sizes: for the purpose of this work, it is important that every cell can approximately be traversed in a single time unit. Depending on size, the i-th cell has a capacity n_i equal to the maximum number of people it can host and, at any given time t, contains some number $y_i^t \leq n_i$ of people. Moreover, depending on street size, a limited amount $x_{ij}^t \leq c_{ij}$ of people can move in the unit interval $[t,t+1]$ from cell i to an adjacent cell j. Finally, depending on scenarios, the network G may consists of a number of maximal connected components: in each component, safe places collectively correspond to a single super-sink 0 with a capacity large enough to host all evacuees.

From each component of the static network G, a dynamic network $G_T = (N_T,A_T)$ is then constructed as the time expansion of G over a time horizon $T = \{0,1,\ldots,\tau\}$, with:

$N_T = \{(i,t)|i \in N,\ t \in T\}$;

$A_T = A_M \cup A_H$, where A_M, the movement arcs, link (i,t) to $(j,t+1)$ for $(i,j) \in A$, and A_H, the holdover arcs, link (i,t) to $(i,t+1)$ for $i \in N$.

Using then x_{ij}^t and y_i^t as decision variables, the model assigns the initial cell occupancy, expresses flow conservation, and enforces the appropriate capacities (possibly considering congestion phenomena). Distinct models are formulated for different τ, with the objective of maximizing the total in-flow y_0^τ in the super-sink at time τ. One then seeks the least τ^* within which the totality of people can be evacuated from the endangered area: to reduce CPU time, τ^* is computed by logarithmic search. In this way, the method provides the decision maker with the Pareto-frontier of the conflicting objectives $\min\{\tau\}$, $\max\{y_0^\tau\}$.

4.2 Parameter Setting and Implementation

The model complexity increases with both τ and the size of G. The more people to evacuate, the larger the τ^*, so the former parameter in turn increases with the number of evacuees. As a city has a scale much larger than a single building in terms of both network and people involved, model size increases accordingly. Just to make a comparison, in the experiments run in (Arbib et al., 2019), G has 116 to 462 cells (depending on accuracy), tests involved 528 to 1,548 evacuees, and computation required from few seconds to less than 100 seconds CPU time. In the case studied here the former values are 12,675 and 26,050, respectively: that is, from almost 30 over 100 times the graph size, and from almost 17 to 50 times the people. Notice that this increase has a double effect, since the nodes of G_T linearly increase with both values, so (see also Section 5.3) in our case we solved problems with over 2,000,000 nodes.

As a consequence, unlike (Arbib et al., 2019), we cannot conceive a real-time application of the model developed, but only its use for scenario evaluation. Particular care is anyway to be taken in parameter setting and other implementation choices in order to limit CPU time and memory usage. For example, we could not model non-linear constraints that relate capacities to actual flows, as their linearization would multiply the number of flow variables by a factor at least 3. We next survey the main model parameters: model granularity, walking velocity, cell capacity, and street capacity.

4.2.1 Model Granularity

Model granularity touches both spatial and temporal units and affects the shape and size of the unit cells in which the network is decomposed, as well as the slots that form the evacuation time horizon. As we assumed in Section 4.1, we embed the crossroad network into a grid, whose cells are assumed to be isometric, that is, they can be crossed in any direction in the same amount of time. This amount helps in the definition of the time slot duration and cells are regarded as virtual unit open spaces that communicate to one another via virtual doors. The virtual door capacities are assumed to be the width of the streets. The geometry of the grid can vary and, due to the structure of the streets, a rectangular grid was used in our study, where each street is split into an integer number of cells.

4.2.2 Walking Velocity

The basis on which the length of each unit time slot was established is the *free flow walking velocity*, that is, the speed at which humans prefer to walk in non-congested and non-hampered conditions. This parameter is important to perceive the distance that an individual can possibly walk during a specific period of time. Through its evaluation one can define the cells in which an area is to be divided for best approximation of traveling time. In literature there are different evaluations of pedestrian free flow velocity, including those depending on their age ((TranSafety, 1997)

(Knoblauch et al., 1996)). Not having this information we assumed a free flow walking speed for a flat surface of 1.00 m/s ((Abdelghany et al., 2005), (Abdelghany et al., 2010), (Abdelghany et al., 2014)).

4.2.3 Cell Capacity

The pedestrian density, which is the number of persons per square meter monitored at any time, is vital information for crowd safety and evacuation performance, as movements are dramatically reduced in highly dense areas. According to UK fire safety regulations, the maximum allowed density corresponds to $0.3m^2$ per standing person, which increases to $0.5m^2$ for public houses, to $1.0m^2$ for dining places, to $2.0m^2$ for sport areas and to $6.0m^2$ for office areas. In our case study, the maximum capacity of each cell is calculated by assuming $0.5m^2$ per evacuee.

4.2.4 Street Capacity

We considered "virtual doors" as the width of the streets. We assume a constant door capacity of 1.8 persons per second per 1-meter door width (p/m/s) meaning that a maximum number of 12.6 persons can pass through a 1-meter street width per time slot (7 seconds). Also capacities are assumed to be proportional to street width.

5 EXPERIMENTS

In order to test the overall methodology presented in this paper on real data, we considered as a pilot study the city of Sulmona in the Abruzzo region of Italy. The dataset used in this experiment was obtained from the ISTAT 2011 census data with the shapefiles from the paper (Di Ludovico et al., 2017)

5.1 Sulmona Datasets

The information about the city of Sulmona is contained in the GIS data extracted from the work of Di Ludovico, et. al (Di Ludovico et al., 2017) about the possible risks to consider during the planning of an emergency. These data relate to the historic center of the city but could be expanded with different or additional data in a second phase.

- Census sections of 2011: The census sections consist of the partition of the entire area of Sulmona into smaller areas with varying characteristics. Each census section has the following information provided. The size (m^2) and the perimeter (m) of each census section, the demography and the socio-economic information of the residents, the type of buildings (whether being used for residential or non-residential purpose), the type and status of the accommodation and occupancy levels. Finally, statistics (such as the seismic design design of the building and the number of floors/interiors and occupants) of each building in these section areas are also provided. Seismic design of the building and the number of floors/interiors

  The census data provided by ISTAT 2011, which includes the whole city of Sulmona, consists of 5300 buildings of which 4246 are used for residential purposes, 778 used for either productive, commercial, directional, tertiary, tourist, receptive, services, churches or others. About 9468 (34%) of the total population (24275) are residents living there. Buildings not used are 5.2% for total assets.
  Finally there is any extensive information about the strategic buildings (those safe buildings that are used by civil protection during the emergency), and public buildings, such as churches, town halls, schools, libraries, etc.

- MSK classification: Which is a measure that stimulates measure that simulates the seismic vulnerability of buildings. This simulation was done by a research of the National Research Council. Every building in the Sulmona has an MSK index (Medvedev, 1977). The area in question, the SISMA project has classified using the MSK model, 15% of class A buildings (buildings with wooden floors and poor or average quality masonry), 66% in class B (poor quality masonry or media and attics in beams or buildings with good quality masonry and wood floors), 5% in class $C1$ (good quality masonry, artificial masonry, with attics in beams or ca) and the remaining 14% class $C2$ (adequate or improved buildings seismically)

- Streets and Road junctions: This shapefile contains information about the streets such as the name, description of the street(road) and the road types (there are only two types, the 'Principale' type, that is the viability that the Civil Protection uses to access Sulmona, and the 'Secondario' type, also used alternatively by civil protection). Also the length (distance between two successive crossroads) and width (three classes, less than 3.5 m, between 3.5 to 7 m, greater than 7 m) of the street is also given.

- Waiting Areas (AT): They are the areas or locations that residents go to incase of any disaster. These areas are identified such as the surface that a person can occupy at a standstill is 2.5 square meters / person. There are also several attributes of these waiting areas such as the maximum number of users that can occupy the Waiting Area – capacity of WA), reduction index of area of the waiting areas. It is an index of reduction of area of the waiting areas which takes into account that there are parts of the waiting areas that cannot be occupied by people, for example due to the presence of trees, bushes, benches, paths, etc.

5.2 Building Sulmona's Network

Since the GIS data and the ISTAT 2011 census data are in different format, a mapping of the two data sets was performed to optimize the data matching/synchronization and minimize the errors. The methodology for network extraction was then applied to the processed data, calling the *City class* which extracts and defines the various attributes of the city such the buildings (i.e (non)residential, strategic, number of residents, etc), waiting areas, streets (main streets and half-streets) and crossroads. Using the *find address* class, the positions (in latitudes and longitudes) of each building is identified and approximated unto the closest street, as well as the MSK classifications.

Figure 6 shows an extract of the city of Sulmona from the GIS shapefiles obtained from (Di Ludovico et al., 2017). The polygons represents the various building units while the red circles represent the cross-roads. The crossroads forms part of the nodes, V_C of the more detailed and generic graph. In order the obtain the remaining set of nodes V_B and V_{WA}, the nodes of the buildings and the waiting areas were derived from their centroids as shown in figure 7. The building nodes has information about the volume of the individual building units. Since the resident population information provided in the ISTAT 2011 data is for the census sections and not for each building, we used the volume of the buildings inside the census section to distribute the population on each building and therefore on each volume. Hence the complete set of nodes for the entire network is given as the combination of the red nodes from the crossroads and the blue building nodes.

Figure 8 gives a visualization of the network of the city of Sulmona with removing all the polygons and replacing them with their centroids. To build the final graph (network), the *City class* needs the (blue) nodes of the building with the arcs (streets) nearest to them. If two or nodes overlap at the same point on the street, a single node is used to represent these set of nodes with a capacity of the total population of residents in the individual overlapping nodes.

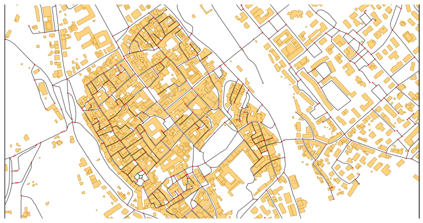

Figure 6: GIS visualisation of an extract of Sulmona city.

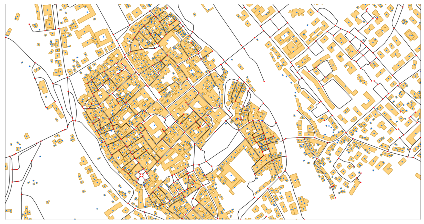

Figure 7: Extract of centroids of building nodes.

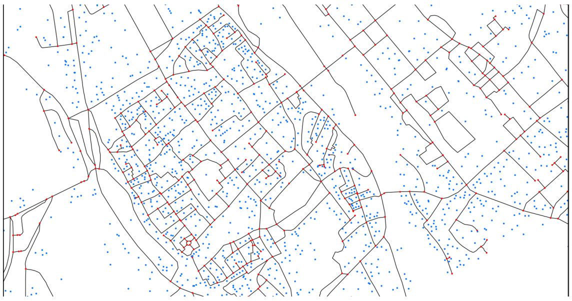

Figure 8: Visualisation of the extracted data without the polygons.

To finally implement the *CityGraph class*, there are two different networks (graphs) that could be generated, i.e,

- The more detailed graph with the set of all nodes (V_B, V_C and V_{WA}) and the streets (E_S and $E_H S$) as the set of all arcs. Figure 9, illustrates a more detailed graph(network) generated for Sulmona. The set of nodes are embedded with all the information about the building, such as the capacity, risk index, type of node, position (usually in latitude and longitude, etc) and the arc set is also embedded with information such as the type of arc (street or half-street), width, length, risk index (which is a function of the set of buildings along that arc), number and list of building situated on that particular arc.
- The generic graph (network) composed of the crossroads (V_C) as the nodes and streets (E_S) as the arcs. Note that this graph is less then as it is made-up of only a subset of the total nodes and arcs. Both the set of nodes and arcs all embedded their respective attributed information.

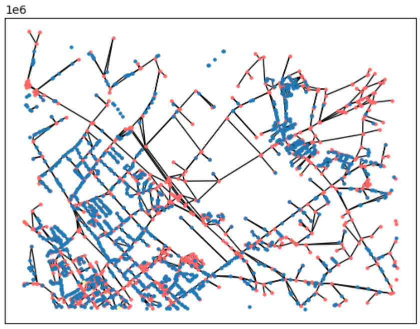

Figure 9: Generated graph for the city of Sulmona.

Both the generic and detailed networks are generated as undirected graphs as we considered the flow pedestrians. Since the algorithm is reusable, it can be adopted to the case of a directed network where the flow is basically vehicles carrying evacuees.

5.3 Sulmona Evacuation plan

Using the dynamic flow model discussed in section 4, we run an experiment to safely evacuate the residents or occupants of Sulmona in case of a disaster. The crossroad network was used, which consists of 920 crossroads (junctions) and 1162 interconnecting streets with different widths and lengths. The streets were split into unit cells, each behaving as a (virtual) quasi-rectangular crossroad that can be traversed in a unit time slot (more details on this aspect follow).

After the splitting, we obtained a graph of 12675 nodes corresponding to the cells of the crossroads and including the super node 0 as safe place, and 25892 arcs linking adjacent cells that allow people to traverse cells. All arcs are assumed bidirectional except the those towards the safe place. A time slot corresponds to the time required for crossing one cell: using average free flow speeds from section 4.2.2 and considering cell size, we determined time slots of 7 seconds. We also considered a street capacity of 12.6 persons through a 1-meter street width per time slot.

We run the simulation of an emergency evacuation planning to evacuate 26050 people who are randomly distributed in the cells. The code for simulation was written in python using the gurobi API and solved using gurobi optimizer version 9.1. All the experiments were run on a Core i7-3rd generation 2.9GHz computer with 16Gb of RAM memory under Windows 10 pro 64-bits.

We run the experiment with two different scenarios: *scenario - a)* that considers 30 safe places and *scenario - b)* with 15 safe places. Figure 10 shows the the minimum time required to evacuate the res-

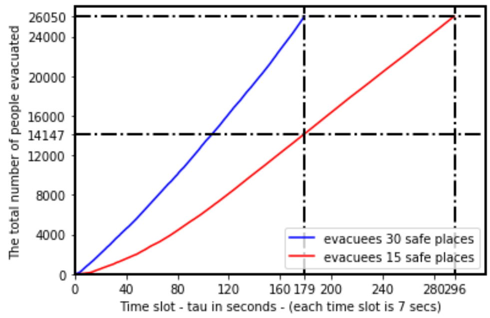

Figure 10: Total number of evacuees at each time slot for two scenarios - (a) 30 safe areas and (b) 15 safe places.

idents in both scenarios. In *scenario - a)*, all the 26050 evacuees were safely evacuated in 180 time slots (i.e., in 1670 secs corresponding to 27 minutes and 50 seconds). In *scenario - b)*, considering the same time slot, only 14147 evacuees were moved to safety whereas, everyone was evacuated in 296 time slots (i.e., 2558 seconds, corresponding in 42 minutes 38 seconds). The total time taken to evacuate all the residents was somehow smaller than what would be expected in real-life. This is due probably because we used a simplified model which does not account for any possible congestion that would occur on along the passages between adjacent cells. The congestion of some arcs could result in bottlenecks thereby reducing the amount and speed flow along those arcs.

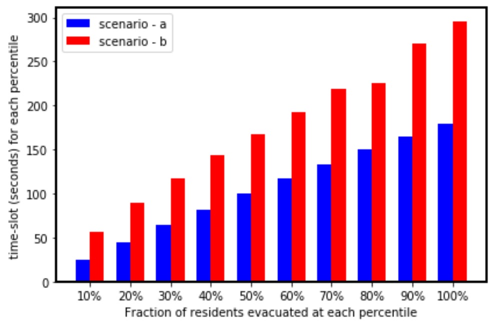

Figure 11: Total time taken to evacuate various fractions/portions of total evacuees for each scenario.

In Figure 11 we report the total time required to evacuate different percentage of the population in both scenarios. For instance, in case of *scenario - a)*, it took 700 seconds to evacuate approximately 50% of the population. Whereas, in *scenario b)* it took 1176 seconds to evacuate the same number of evacuees. Looking at the figure, there seems to be a quasi-linear relationship between the number of safe places and the total time needed to complete the evacuation process,that is, it takes approximately twice the time needed to evacuate residents in *scenario - a)* to evacuate the same number of residents in *scenario - b)*. For instance, 60% of the total evacuees were evacuated at time slot $tau = 117$ in *scenario - a)* while 30% of the total evacuees were evacuated in the same time slot $tau = 117$ for *scenario - b)*.

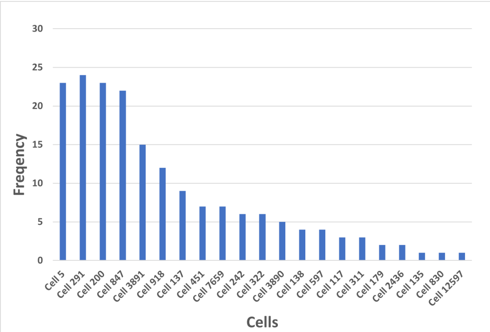

Figure 12: The number of times a cell has the maximum capacity in all the time slots.

Finally, we also analysed the impact of certain cells in the evacuation process. Using *scenario-a* we computed the cells (excluding the super-sink) which had the maximum capacities at each time-slot throughout the entire evacuation process of 179 time-slots. As it can be seen from Figure 12, cells *3, 291, 200, and 847* respectively had maximum capacities of *23,24,23 and 22* in different time slots out of the 179 ones. Also there were 15 different times slots (out of 179) that *cell 3891* had a maximum capacity during the evacuation process. This figure tells us that the model we used could not be adequate, especially for cities with higher population density. In fact, the model we used does not consider congestion in the cells during evacuation. The congestion can have sever impact on the time needed to evacuee all the population.

On the other end, the results we obtained so far, using a simple optimization model, tell us that we cannot do better in Sulmona city historical center and that the number of safe places available in the city affects the total time needed to evacuee the entire population, in fact the more the safe places, the shorter the population evacuation time.

6 CONCLUSIONS AND FUTURE WORK

The contribution of this paper was threefold: *i)* the definition of a new algorithm able to generate an enriched network from GIS data, specifically tailored to include useful information for emergency management, *ii)* the adaptation of the optimization model developed by (Arbib et al., 2019) to outdoor scenarios, that is the evacuation plan of a city in case of natural disaster; *iii)* the validation of the previous step to a real case study, i.e., the historical centre of Sulmona city in Italy. The network generation from GIS data is able to generate a network representing the city map in terms of buildings, crossroads and streets. Different from other similar algorithms, we are able to manage additional information, needed for evacuation planning, added as attributes to network nodes and arcs. For what concerns the evacuation model, we adapted the linear optimization model originally developed by (Arbib et al., 2019) for building evacuation. The model had to be customized with respect to several parameters, and re-scaled to the network of several orders of magnitude. In the case study of Sulmona, we solved the problem with over 2,000,000 nodes. The large scale required forced us to consider, for a first approach, various simplifications and only a limited amount of the information supplied by the network. Although some work should then be devoted to extend the model, the results obtained are however encouraging in terms of the approach viability.

As future work, we plan to extend both the network construction and the optimization model in order to manage more real situations. In particular, we are working to make more general the network to use it in other relevant problems, such as pre- and post-disaster facilities planning, and post-disaster reconstruction planning (Mudassir, 2020). We also aim to find a more reliable estimate of the people who are in a building by considering that during the day the number of people in the structures changes (for example, children at school and working shift). Among the different methods, using GPS tracking might be a satisfactory solution to retrieve a more realistic population distribution (No et al., 2020).

For what concerns the optimization model, we aim to add the congestion that will approximate the non-linearity of the arc capacities. This will affect the speed the system empties modelled as a decreasing function of the cell occupancy. A more accurate model of congestion requires arc capacity to be a concave decreasing function of cell occupancy. Finally, we aim to make a trade-off analysis between the number of safe places and the total evacuation time. This will be very useful for pre-disaster evacuation plan definition.

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