Impact of network structures on emergency services - Examples from Germany

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Extended Abstract

Planning problems for Emergency Medical Services (EMS) span from strategic to operational decisions and are usually informed by historic demand. The first model to locate ambulance bases was introduced by Toregas et al. in 1971 [1]. The Location Set Covering Model (LSCM) determines the minimum required number of bases and their locations to cover the entire region within a fixed time threshold. Another important model is the Maximum Expected Coverage Location Problem (MEXCLP) by Daskin that explicitly takes the coverage depending on the expected busyness of the ambulances into account [2]. Relocation approaches are applied at the operational level of EMS planning and determine short-term locations for ambulances. Gendreau et al. (2001) proposed one of the first real-time ambulance location models [3]. Reviews on ambulance location and relocation models can be found in [4] for example.

Many models assume an underlying graph or network with nodes representing demand and possible base locations. Edges are weighted by the driving times between the nodes. Other approaches assume a grid structure for the underlying city/region. It means that the city or region is divided into equally sized squares, e.g., of $1km^2$, or if possible hexagons. Each square or hexagon presents a demand location, and a subset contains the potential base/ambulance locations. Often, Euclidean distances are used for these approaches, and distances are measured between the centres of the squares or hexagons. For example, Chanta et al. (2014) presented a bi-objective coverage location model that is solved for a data set with grid structure [5]. Several relocation approaches also use a grid structure, e.g., the multiperiod set covering location model for dynamic redeployment of ambulances by Rajagopalan et al. [6].

Many of the published models are tailored to individual settings rather than being tested for a range of heterogeneous supply and demand configurations. Despite some first analyses, it is still unclear whether suggested planning approaches work equally well for different demand structures, e.g., rural versus urban areas, when /if network or grid structures are more efficient, and when to best use which planning approach. Therefore, we have developed a framework to help set up testing instances for location problems in EMS logistics. The purpose of this framework is to capture differences in demand structures and EMS systems and also to allow researchers to benchmark newly developed approaches. We also developed a first data set with the network and grid structure for several German cities and rural areas. As some instances are developed for both structures, it is possible to compare approaches that use either one of the structures.

Figure 1 shows both structures for the city of Stuttgart as one example from the data set. First, we have the city map showing the 148 districts and the chosen representation points. These points then form the network. Figure 1 b) shows only a subset of the 3225 edges in the network for distances below a maximum driving time of 15 minutes to make the general structure of the network visible. For the grid structure, the demand was set according to the population density in each square. Other parameters that describe the instances include: (1) the possible locations for bases, (2) the number of emergency medical vehicles, in total, and for each possible base location separately, (3) the time threshold(s) for the response time, and (4) parameters that are only needed for a subset of models such as busy fraction(s), service level(s) and reliability factors.

In this talk, we outline the framework and data sets, present first results and findings, and discuss implications and open topics for future research and practice. We also touch on ethical aspects as while the research originates from the logistics and operations research field, implementing findings in practice can impact emergency care for patients. Due to limited resources, it is often not possible to cover 100% of the demand within the response time. Although this is already the case today, applying the mathematical models increases the transparency and as a consequence the need to think about this fact more carefully. In addition, unknown or unwanted biases in input demand patterns must be prevented while acknowledging that different age groups (or other demographic and sociographic aspects) could have varying demands.

References

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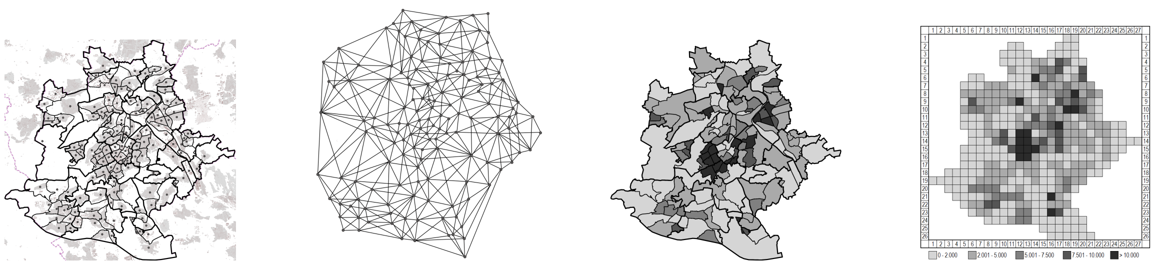

(a) Map and districts (b) Network structure (c) Population density (d) Grid structure

Figure 1: Stuttgart instances