Towards the Design of a Simulation-based Decision Support System for Mass-Casualty Incidents

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ABSTRACT

In case of a mass-casualty incident, e.g. due to a disaster, a high number of patients need medical care within a short time frame and often, a significant percentage must be transported to a hospital or another suitable care facility. Then, different mass transportation modes (e.g., busses, ships or trains) may be used to quickly transport patients to available medical treatment centres outside of the disaster area. Within the SimPaTrans project, we develop a simulation-based decision support system for locating, sizing and analysing different modes of transport in order to prepare for mass-casualty incidents in Germany. In this paper, we present the outline of the tool as well as a first optimisation use case for transportation patients within the city of Karlsruhe, Germany.

Keywords

Mass-casualty incidents, simulation, multicriteria decision making

INTRODUCTION

Over the past five years, worldwide more than 300 natural disasters resulting in over 100,000 people requiring immediate assistance respectively were recorded (EM-DAT et al. 2022). In addition to natural disasters, man-made disasters such as organised violence have been posing an increasing threat to the population (Davies et al. 2022). Along with recent events in Ukraine, these trends have raised awareness to prepare for potential upcoming disasters and (man-made) mass-casualty incidents (MCI), which are defined by a high number of casualties requiring medical treatment. The complex and time-critical logistical problem of providing adequate medical care to such a sudden increase in patients is even aggravated by potential damages to local infrastructure, exacerbating a shortage in capacity for medical treatment. As a result, transporting casualties to more distant medical centres (e.g., hospitals) may be required.

To address this problem efficiently, different mass transportation modes (e.g., busses, ships or trains) may be used to quickly transport patients to available medical treatment centres outside of the disaster area. Seriously injured casualties, however, may require modified or specially equipped transportation vehicles. While the procurement of these adapted transportation vehicles may require several years, disasters usually have a very short lead time (if any). Hence, planning is crucial to be able to respond properly to a disaster (Othman, Zoghlami, et al. 2014). Thereby, multiple decision levels are addressed. At a strategic level, the fleet size must be determined based on potential scenarios and is usually restricted by a limited budget. To be useful in practice this (limited) fleet must be available as quickly as possible. Therefore, the individual vehicles should be stationed carefully so they can reach patients at future disaster sites quickly. When a disaster occurs, it must be decided on the operational level if and which

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vehicles are to be sent to disaster sites and patients need to be allocated to suitable vehicles as well as appropriate medical facilities.

In literature, disaster management is often described as a cycle consisting of four phases: mitigation, preparation, response and recovery (Altay and Green III 2006). While the first two phases include pre-disaster tasks such as facility location or stock-propositioning, the latter two describe actions performed while and after a disaster has hit, such as distributing supplies or managing casualties (Caunhye et al. 2012). Hence, each phase brings its own challenges, potential actions and decisions, with tasks in the post-disaster stage depending on actions performed in the pre-disaster stage. With that variety of problems, the field has been widely studied in the literature. An early review is provided by Altay and Green III (2006) and Caunhye et al. (2012).

Among the tasks to be performed before and after a disaster, one of the most important ones is casualty management (Farahani et al. 2020). Mostly performed in the response phase, it covers all activities necessary to save as many lives as possible (Dean and Nair 2014). However, with many casualties to be treated while resources are limited, several logistical challenges occur and decisions must be made. Farahani et al. (2020) provide an extensive literature review, clustering these challenges into five different stages: dispatching of resources/search and rescue followed by the on-site triage and on-site medical assistance, the transportation to the hospital and the hospital triage/comprehensive treatment. Although these five stages can be well distinguished from each other, multiple papers have linked several of them in their models. For papers addressing casualty management until 2019, the reader may refer to Farahani et al. 2020.

SimPaTrans is a project commissioned by the German Federal Office of Civil Protection and Disaster Assistance (BBK) with the aim of developing a decision support system (DSS) that allows for preparing for and responding to potential mass-casualty incidents resulting from both, natural disasters as well as organised violence. The DSS combines mathematical optimisation and agent-based simulation to quantify, visualise and analyse different scenarios subject to available resources such as transportation vehicles, (temporary) medical centres or depots and different patient categories with changing health status. While the DSS is mainly oriented to assist at the strategic and tactical levels to support decisions regarding the infrastructure, it can also be used on an operational level to determine optimal allocations and routes during an actual crisis.

In our research, we aim to support both, long- as well as short-term decisions in casualty management. For this purpose, we develop a simulation-based DSS, that should assist with proactive decisions such as major investments as well as guide allocations and vehicle routing in a disaster's aftermath. The overarching aim in all phases is to maximise the number of survivors by optimising service order, transportation and allocation. To meet this goal, we incorporate different severity levels of injury as well as their corresponding survival probabilities.

The remainder of the paper is structured as follows: In the next section, we present the relevant literature, followed by a description of the simulation framework. We then evaluate the DSS with a preliminary case study and conclude the paper in the last section with a brief summary and an outlook on the following research.

RELATED WORK

One commonly used methodology for decision-making in disaster relief logistics is mathematical modelling (Lechtenberg et al. 2017), allowing to determine optimal solutions for decision problems. Shin and Lee (2020) present a stochastic model for patient prioritisation and hospital selection, addressing the on-site triage and transportation to the hospital. Their objective is to maximise the expected number of surviving casualties with a decreasing chance of survival as time passes by. However, they limit their model to patients requiring medical treatment in a hospital and do not consider casualties with minor injuries, who may only require on-site medical treatment. Caglayan and Satoglu (2021) present a multi-objective two-stage stochastic model to minimise the number of unserved casualties, the second decision referring to the number of ambulances required, being at the border of the preparation and response phase. Majzoubi et al. (2021) do not explicitly model a disaster scenario, but a demand surge in emergency service vehicle routing. They aim to minimise the total time travelled by all vehicles, under the constraint that each patient must be served within a specific time window. However, their model can only partly be applied to disaster management, since they assume that each ambulance only serves up to two patients, which is not necessarily the case in a mass-casualty event. Sun, Wang, Zhang, et al. (2021) present a robust optimisation model in which they combine facility location and transportation to the hospital. They aim to minimise the weighted Injury Severity Score (ISS) over both types of casualties (mild and severe), constrained by the available resources. Sun, Wang, and Xue (2021) extend the model of Sun, Wang, Zhang, et al. (2021) and present a bi-objective robust optimisation model, in which they link emergency facility location, emergency resource allocation and casualty transportation planning. They aim to minimise the sum of the ISS over all patients as well as the costs occurring for temporary logistics restricted by limited resources. However, they do not include any on-site medical service. Rezapour et al. (2022) incorporate the search and rescue phase by rejecting the assumption of all casualties being present and known at the beginning but assuming that they arrive over time. They maximise the number of expected saved casualties over time, restricted by the capacities of on-site medical services (OMS). Aringhieri et al. (2022) present in their paper a model combining on-site medical service for both, mild and severe patients, ambulance routing and hospital selection. They aim to minimise the maximum completion time for severely injured casualties while maximising the weighted number of mildly injured patients.

Besides mathematical optimisation, another, still less frequently used methodology is simulation (Lechtenberg et al. 2017). An overview of agent-based simulation models for emergency response is provided by Alotaibi and Ibrahim (2018). Na and Banerjee (2019) simulated evacuation actions resulting from a disaster, including different types of transport for different degrees of injuries as well as private vehicles based on geographical information system. Their objective was to determine facility locations as well as the allocation of casualties to vehicles and medical centres. More recently, Jat and Rafique (2020) applied simulation to test different strategies for patient-hospital allocation varying in complexity and interaction between the incident site and the medical facilities.

Both methodological approaches can and should be incorporated into a DSS to support decision makers and experts in practice to prepare for MCI. An early overview of existing papers addressing DSS is provided by Ortuño et al. (2013), followed by a review of existing research on decision support in disaster management by Lechtenberg et al. (2017). In recent literature, relatively few papers can be found presenting DSS in emergency management. Fikar et al. (2016) present a DSS for supply distribution using both, traditional vehicles as well as unmanned aerial vehicles (UAV), while Othman, Zgaya, et al. (2017) provide a three-level DSS for optimal deployment of resources as well as their supply. They include mathematical optimisation and agent-based simulation to address the complexity that arises after a disaster. However, both DSS are not directly linked to casualty management. This gap is partly addressed by Çağlayan and Satoglu (2022), who present a tool to track the patient flow from on-site triage to hospital treatment and monitor relevant parameters. However, the system's objective, different from a DSS, is to facilitate information transmission (Çağlayan and Satoglu 2022) rather than support the decision-making process (Jung et al. 2020). This paper addresses the gap in DSS for casualty management. By incorporating mathematical models as well as agent-based simulation "allow[ing] the decision-maker to assess the performance of different alternatives" (Lechtenberg et al. 2017), we provide an extensive tool to support decisions at all stages of casualty management.

DECISION SUPPORT SYSTEM

Within the simulation framework, the response phase is addressed and scenarios for mass-casualty incidents can be modelled and analysed. For each scenario generation, the numbers, locations and injury patterns of patients must be defined, together with the availability of hospitals and information of modes of transports and corresponding networks, including potential disruptions. In a run, patients who need transport are allocated to transport modes and are then transported to the assigned hospitals, depending on the available resources. Expert interviews and workshops with German governmental employees, the German army, rescue services, etc. form the practical bases of the tool, including information on patient categories and corresponding survival probabilities.

Simulation framework

The consideration of uncertainties in DSS is becoming more and more critical due to increasing dynamic complexity. Uncertainties manifest themselves at the level of operational management, since measures can influence each other adversely (e.g. bottlenecks), unforeseen dynamics and interactions between subsystems can drastically reduce the quality of decisions made (e.g. feedback loops, Helbing 2013). Uncertainties also appear at the level of strategic planning, when it is necessary to estimate changing boundary conditions or to assess future incidents with respect to their probability of occurrence and impact. Assuming that these uncertainties are handled, the analysis of feasible solutions is anything but unambiguous, if preferences of decision makers are varying.

The FRAMESS ('FRamework for Analyzing SysteMic Risks and Exploring Sustainable Solutions') platform developed at the Karlsruhe Institute of Technology provides a means and basis for integrated analyses. FRAMESS addresses the challenge of the above-mentioned uncertainties by providing a specialised agent-based simulation engine, which offers interfaces for complex optimisation, and integrates a module for multi-criteria decision analysis (MCDA). Optimisation refers on the one hand to the identification of (robust) measures in crisis management, but also to the identification of (robust) infrastructure planning, e.g. when it comes to the question of ideal asset locations for effective crisis management.

Based on an agent class template, new entities of a system to be simulated can be integrated relatively elegantly without the need for rework in other FRAMESS modules, e.g. optimisation. With this modelling approach and

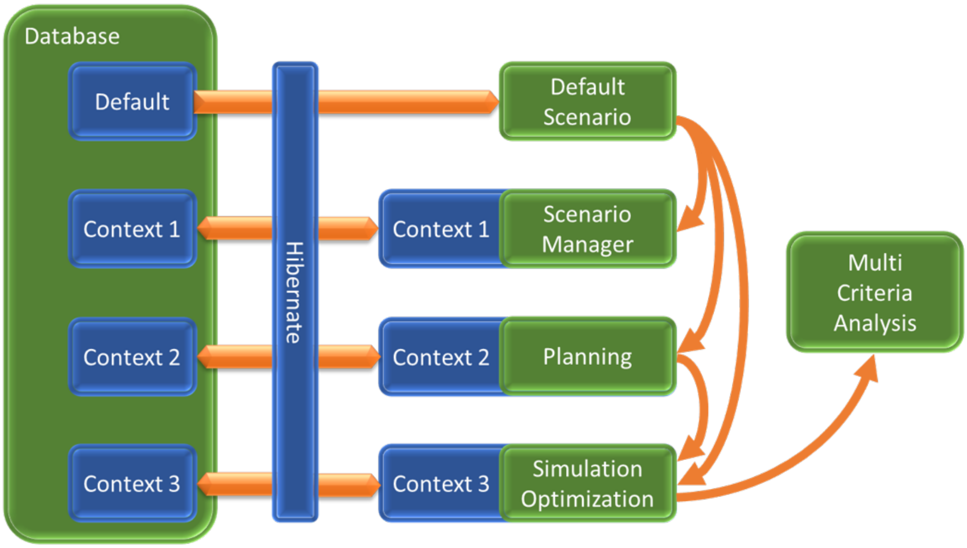

Figure 1. FRAMESS application modes.

the modular FRAMESS architecture, continuous model integration, re-scaling and re-parameterisation are readily implementable, qualifying FRAMESS as a platform for sustainable decision support and scientific investigations. FRAMESS is divided into three layers: database, application and front-end. An essential component in FRAMESS is the database. The database is where decisions are made about which entities are relevant to the simulation, what the model granularity is, what evaluation criteria are used, what resources exist, and what the environment is in which the agents reside. All the mentioned objects are customisable and already by relational database properties maximum consistency is taken care of in the FRAMESS database, so that error-proneness in complex simulation models is minimised.

From a functional perspective, FRAMESS is divided into three basic modes (Figure 1), which allow different users to work on different questions independently of each other. Against the background of the uncertainty issues mentioned above, the scenario manager (Context 1) allows a flexible parameterisation of disturbance and load, which in turn can be persistently stored in the database, to be used for simulations (Context 3) and for MCDA analyses. Thus, different hypothetical future scenarios can be investigated. In the scope of this work, disruption is modelled by parameter modification of environmental variables such as transportation infrastructure, or already instantiated agents such as transportation entities, healthcare facilities, and cities, and strain is modelled by generating patient agents with selected injury patterns at specific locations.

Based on scenarios, the planning mode (Context 2) allows to persistently insert new entities, e.g. transport agents, and simulate a specific scenario based on them. Disturbance and load scenarios can in turn be defined on the basis of planning scenarios.

A publication presenting results generated using FRAMESS addresses the topic of AI-based early warning (Möhrle et al. 2021).

Optimisation

The problem setting requires multiple decisions on various decision levels. On a strategic level, governmental organisations must decide on a suitable fleet size for adapted mass-transportation vehicles such as specially equipped trains, aeroplanes or vessels. Since these decisions must be made well in advance, uncertainty plays a non-negligible role and should be incorporated into the decision process. Once purchased, the vehicles must be located at some place. In the case of an emergency, they should be available as quickly as possible, thus a stationing close to potential disaster zones is advantageous. However, vehicles stationed too close to a disaster zone risk being damaged or enclosed themselves. Hence, stationing a vehicle should be a trade-off between centrality and a location's vulnerability.

Once a disaster hits an area, two main decisions arise. First, the order of serving and transporting the patients must be determined based on the triage. Linked to that, more severely injured patients must be allocated to a hospital. Since local hospitals may not have sufficient capacity to serve all patients, some patients might be required to be transported to a more distant hospital. Thereby, various modes of transport can be incorporated, based on a patient's health condition. However, in contrast to street-bound vehicles such as ambulances and (to a certain extent) busses, vehicles such as trains and aeroplanes may not be able to directly access the disaster site to provide first medical services or pick-up patients for transportation. Therefore, street-bound vehicles must not only transport patients from the disaster site to a medical centre but also serve as a shuttle between the disaster site and train stations or airports. Hence, before allocating patients to transportation vehicles and hospitals, ambulance routing is a crucial action to be considered.

An exemplary optimisation model to be integrated into the DSS is the model presented in Aringhieri et al. 2022, in which the authors optimise ambulance routing in a post-disaster stage while considering fairness between groups. Thereby, they distinguish between two different patient types, more severely injured (red) patients and less critically injured (green) patients. While red patients must be taken to a hospital for further treatment, green patients only require on-site treatments. However, some green patients require medical services more urgently than others, which is reflected in an individual priority score, with a higher priority score denoting higher urgency. Patients can be served (and transported) by any ambulance on its tour. In this process, each ambulance can treat green patients on its way to a red patient, but may not stop for treatment when having a red patient on board. While all red patients must be visited (and transported), green patients can also be left untreated. As the tour for each ambulance is restricted by a maximum tour duration, this problem setting leads to a trade-off between providing treatment to as many green patients as possible while minimising the red patients' waiting time.

Since Aringhieri et al. (2022) do not incorporate multi-modal transportation in their model, we extended the scope and included transportation hubs (e.g., train stations), where red patients are gathered to be subsequently transferred to a more distant hospital. Thus, red patients can either be brought directly to a hospital (where they receive treatment immediately) or allocated to a transportation hub for further transfer. This extension leads to an additional trade-off for serving red patients: While a decision maker may aim to transport patients to the hospital as quickly as possible to start treatments (resulting in sooner idle capacities to treat additional casualties), such a prioritisation would lead to an additional delay of treatment for patients being transferred to further distant hospitals.

To incorporate these trade-offs, three different benchmarks are introduced. Following Aringhieri et al. (2022), the efficiency of treating green patients is calculated as the sum of their priority scores (σ_G), while for red patients, the maximum completion time (C_{max}) is considered to account for between-group fairness. However, different from Aringhieri et al. (2022), we distinguish between the maximum completion time for patients being brought to a hospital (C_{max_h}) and the those being brought to a transportation hub (C_{max_t}). By doing so, we incorporate the trade-off of starting treatments quickly in both, more distant as well as local hospitals to account for within-group fairness.

Components

Casualties

We assume that a mass-casualty event can occur in large cities (cities with more than 100,000 inhabitants) across Germany depending on the scenario. Thereby, the number of casualties is assumed to depend on a city's exposure, which is characterised by various factors such as population size, political and economic relevance or geographical characteristics. Restricting the potential locations to cities with more than 100,000 inhabitants may exclude scenarios such as major events being held in smaller cities. In that case, a decision maker could consider including that particular location in the simulation and treat it as if it had more than 100,000 inhabitants. Besides the actual number of casualties, injury patterns (and thereby an injury's severeness) can vary, such that different modes of transport and medical centres may be eligible.

Based on the injury pattern, a corresponding survival function is attributed to each patient. The survival function is initialised at the time of the incident and decreases at a certain rate over time, indicating a patient's health status at each point in time. Based on that status for a given point in time, a patient will be prioritised accordingly.

Infrastructure

The infrastructure for transportation is represented by a (connected) graph, with edges representing streets, rails or waterways, and nodes representing intersections, railway stations, airports or harbours. The geographical data is based on OpenStreetMap (OpenStreetMap contributors 2017) and contains information such as the number of lanes, the number of rails or platforms, the runway's length or the river's depth. However, depending on the scenario, segments of the transportation network may be reduced in capacity or completely inaccessible. Therefore, a subset of links and nodes on each distinct transportation network can be selected and reduced in capacity to properly represent a scenario's impact. It is also possible that all edges of certain types, e.g. airways, are unavailable to model that the airspace is closed.

The data for permanent medical centres (i.e., hospitals) are based on the directory of hospitals and prevention or rehabilitation facilities 2020 (Statistisches Bundesamt 2022) as published by the Federal Statistical Office. The maximum available capacity per specialisation and the exact location are retrieved from the directory. Yet, the available capacity to treat injured people is limited by a hospital's basic load of patients, depending on the season. Moreover, if a medical centre is located in an area hit by a disaster, capacities may be additionally limited e.g., by a shortage of supplies (or staff), potential damage or threat.

Modes of transport

In contrast to most of the existing publications, patients can be transported by multiple modes of transport in our work. Besides traditional ambulances and helicopters, we also include (adapted) busses, trains, ships and aeroplanes. As mentioned in the paragraph on infrastructure, a graph including edges for all streets, rails or waterways with corresponding distances and geographical information is used as a base. Depending on distinct transportation networks different modes may be eligible. While a severely injured patient may only be transported by ambulance and helicopters, minor injured patients could also be transferred in (slightly adjusted) busses, trains or ships, allowing for a more efficient (faster) evacuation of the disaster zone. The SimPaTrans tool enables users to dimension, analyse and compare different modes of transport, either as alternatives in different runs or in combination.

FIRST EXPERIMENTS

Experiment settings

To provide first insights into the tool's functioning, a case study is presented. The case study is based on the model as presented in Aringhieri et al. (2022), extended by transportation hubs as described above. Hence, the mode of transport used for simulation is restricted to ambulances, for transportation hubs we consider train stations only and ignore airports, harbours, and bus terminals for now. As described above, we restrict the patient groups to two – slightly injured (green) patients and severely injured (red) patients.

For the case study, we consider a disaster in the city of Karlsruhe. The city is located in the southwest of Germany in the state of Baden-Württemberg, close to the French border. In the case of a disaster, we assume that 0.1% of the population of Karlsruhe is affected (meaning they require at least some minor medical service), resulting in 307 casualties (Bundesamt 2023b, based on the data for 2021). Thereof, 20.0% are severely affected, resulting in 62 red patients and 245 green patients. At the beginning of the disaster, we assume that the casualties are equally spread across an area of approximately 0.2 km^2 in the city centre. To treat the patients, 4 hospitals are available, with a total of 200 trauma beds (Statistisches Bundesamt 2022). However, since on average 77.2% of the beds are occupied (Bundesamt 2023a), only 44 beds are idle. Thus, at least 18 red patients cannot be served locally, but must be transferred by train to other hospitals. To transport these casualties to more distant hospitals, we assume a relief train to be stationed at the main station, allowing transport for 50 patients. Distances are retrieved from FRAMESS based on the street network. For calculating the travelling times we assume an average travel speed of 30 km/h to account for narrow streets in the city centre as well as disruption in some parts due to the disaster. The number of ambulances is estimated based on the total number of ambulances in the state of Baden-Württemberg (Kraftfahrt-Bundesamt 2023) and scaled by the population of Karlsruhe, resulting in 69 ambulances. Since not all ambulances might be available due to several reasons, we reduce the number by 20% resulting in 56 ambulances. Therefore, each ambulance has to transport on average 1-2 red patients and serve up to 5 green patients. The maximum operating time for ambulances is set to 150 minutes, the service times for patients follow a uniform distribution and take between 10 - 40 minutes for green patients, while red patients require 10 - 55 minutes of service time (Qualitätssicherung im Rettungsdienst Baden-Württemberg 2021). The service time per hospital is set to 2 minutes (Gräff et al. 2020), assuming equal service times in all hospitals and train stations. As in Aringhieri et al. (2022), green patients vary in urgency, approximated by priority scores. We thereby follow the authors and assume equally distributed priority scores of 5, 10 and 15.

Interim results

The case study was implemented and run on an Intel Core i7-1185G7 with 3.0 GHz and 16 GB. The optimisation at the algorithm's beginning was solved using IBM ILOG CPLEX. The results are depicted in Table 1.

The results show that for the given scenario, all red patients can be served within two hours. When increasing the number of iterations, the maximum completion times can even be decreased. Besides that, the algorithm also improves the sum of priority scores of green patients served σ_G with an increasing number of iterations, as visualised in Figure 2. However, this comes at the cost of run time. Already with relatively few iterations, the total run time exceeds two hours (Figure 3).

Table 1. Preliminary results

Run	*Run time (sec)*	*Max # iter*	*Tabu*	$\sum$ *trav. time*	C_{max_h}	C_{max_t}	σ_G
1	7376.3	60	10	787.11	112.91	74.42	525
2	10062.9	60	5	801.80	110.38	71.47	540
3	15349.9	100	10	775.87	107.69	71.67	630
4	17128.5	100	5	788.76	92.57	74.42	640
5	21316.0	120	10	754.19	102.71	72.21	685
6	21587.2	120	5	771.96	98.15	68.23	680
7	31624.9	200	10	752.73	97.69	64.23	905
8	32515.7	200	5	772.74	88.25	66.25	835

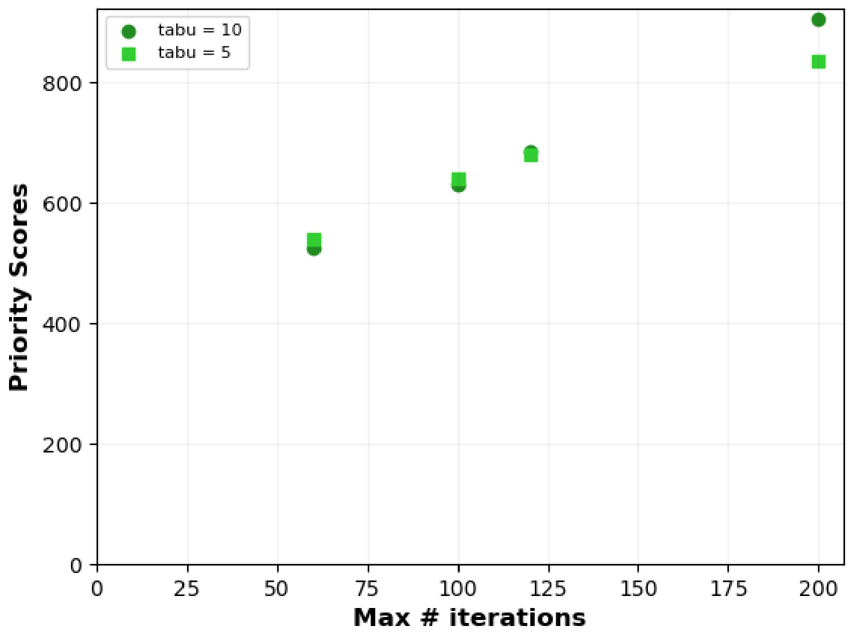

Figure 2. Sum of priority scores depending on the maximum number of iterations

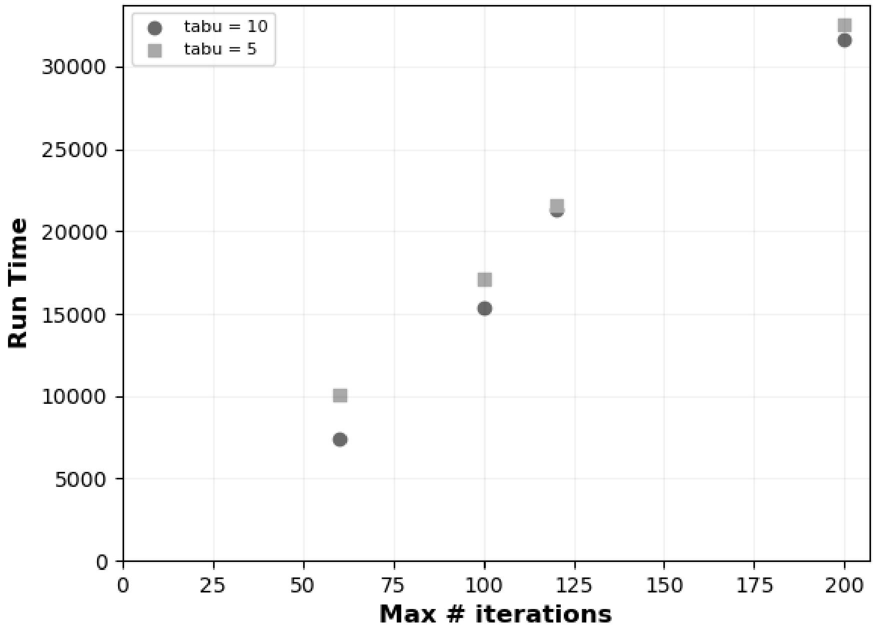

Figure 3. Run time depending on the maximum number of iterations

The optimisation is only the first part of the process of supporting the decision making. Eventually, the results obtained serve as input for the following simulation. In doing so, we want to account for aspects such as the dynamic availability of beds, varying status of streets (closed, disrupted or fully accessible) as well as variations in parameters such as the available number of relief vehicles (including both, the vehicles themselves as well as available drivers), medical staff for on-site treatment as well as further treatment in medical centres or casualties.

CONCLUSION AND OUTLOOK

This paper provides an outline of the SimPaTrans project and the tool that will be developed for this purpose. Being built generically, it can be applied to other regions and countries and serve as an assistant to prepare for large-scale disasters on the strategic, tactical and operational level. In a case study for the city of Karlsruhe, we demonstrated the DSS's usage and pointed out future steps to be taken to support decision makers. However, the case study also shows the challenges of existing heuristics applied to larger instances and the resulting need in developing efficient approaches with shorter run times.

In future work, we aim to incorporate the remaining nodes of transport (waterway and airway) into a model. Additionally, we will include the actual planning and scheduling of patient transports to more distant hospitals. Based on interviews and workshops with (medical) experts from e.g. hospitals, emergency services or different care organisations, we will extend the patient categories to representative injury patterns and include more elaborate survival functions for all injury patterns. Regarding the hospitals, a distinction will be made between different seasons to account for varying basic loads and based on the injury patterns, more precise patient-hospital allocations will be incorporated. We also plan to take into account the varying availability of staff at different locations and consider moving medical staff between locations to improve the quality of treatment. To incorporate the before-mentioned uncertainties, we aim to extend the optimisation models to include stochasticity on various stages and analyse the results using simulation.

Even though the DSS is primarily designed to assist before a disaster hits and thus computation time is not the most critical factor, the case study has shown that even for smaller instances such as the city of Karlsruhe, heuristic approaches can require long computation times. Therefore, in future work, we plan to develop time-efficient heuristics for casualty management that take different transport modes and patient categories into account.

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