Simulating Casualty Transportation and Allocation Policies for Mass Casualty Incident Scenarios

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Abstract

During mass casualty events, fast medical care must be provided to often many affected individuals. When resources like ambulances are limited, decision makers may need to consider incorporating mass transportation vehicles to assist with transportation. With time being a crucial factor, on-field decisions are typically based on practical and straightforward policies, such as sending casualties to the closest hospital until the capacity limit is reached. However, the integration of mass transportation vehicles necessitates a re-evaluation of these conventional policies. Therefore, this study aims to develop and evaluate various casualty transportation and allocation policies during mass casualty incidents using discrete-event simulation. An important feature of this study is the differentiation between life-threateningly and severely injured casualties. Life-threateningly injured casualties require immediate transportation to a hospital, whereas the latter can be considered stable enough to be transported using alternative modes of transportation, freeing up ambulances and decreasing overall transportation times.

Keywords: Discrete-event simulation, mass casualty incidents, mass transportation vehicles

1. Introduction

In recent years, Germany experienced several mass casualty incidents. In June 2022, for example, five people died and 40 were injured during a train accident in Garmisch-Partenkirchen. The flooding in Rhineland-Palatinate and North Rhine-Westphalia, especially in the Ahrtal region, in 2021 lead to more than 180 casualties and over 700 people injured. The incident stretched over a large region and the high number of people being injured and/or without housing meant a big challenge for decision makers, fire and rescue services and politicians. As several hospitals were affected as well and resources were scarce, transportation of casualties presented an additional challenge. Experts believe that Germany, but also other countries worldwide, need to expect an increase in natural disasters in the future (ZDF, 2022).

In general, to increase transportation capacities when resources such as ambulances are limited and casualties might need to be transported to more distant hospitals, decision makers may consider including mass transportation vehicles (e.g. trains) to take over parts of the transportation. By doing so, ambulances would not be required to cover the full distance from the disaster site to the selected hospital but to only transport the casualty to a transfer point close to the disaster site (such as train stations, airports or harbours). Such a setting may change optimal hospital allocation strategies. Instead of choosing the closest hospital to keep transportation times as short as possible, further distant hospitals with a very short distance being covered by ambulance may be preferable. Besides the hospital allocation policy, a split transport may also affect the transportation priority policies. While being transferred between different transportation vehicles may be considered for severely injured but relatively stable casualties, life-threateningly injured casualties may not be stable enough to be transported by several different transportation vehicles, such that the ambulances must cover the full distance. This can lead to a trade-off for decision makers when distinguishing the transportation priority. On the one hand, priority should be given to life-threateningly injured casualties, such that they can receive medical treatment in a hospital

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as soon as possible. On the other hand, prioritising casualties with a short distance to be covered by an ambulance - this policy is also known as the shortest processing time (SPT) policy - may reduce overall waiting times and therefore increase overall survival probabilities, but could result in a delay for hospital treatment for life-threateningly injured casualties.

The aim of this study is to assess the effectiveness of different hospital selection and casualty transportation policies when including additional transportation modes. In order to do so, we propose and implement a discrete-event simulation and perform an extensive evaluation based on a set of scenarios. As an important feature of this study, we differentiate between life-threateningly and severely injured casualties. While life-threateningly injured casualties must be transported directly to a hospital, severely injured casualties are considered to be stable enough to be transported using alternative modes of transportation, freeing up ambulances and decreasing overall transportation times.

This paper is structured as follows: in Section 2 we provide a brief overview of the current literature, followed by a description of the methodology in Section 3. Section 4 introduces the experimental settings and scenarios, before the results are presented in Section 5. We conclude the paper with a summary and an outlook on future research in Section 6.

2. Literature review

Within the literature on emergency management, a significant stream focuses on the provision of care for casualties during mass casualty incidents (MCIs). The field of casualty management encompasses several key actions (Farahani et al., 2020; Rezapour et al., 2022). Initially, prompt rescue or evacuation of casualties from the disaster site is essential, followed by triage procedures that prioritise them based on their initial health status. Subsequently, casualties are typically stabilised before being transported to medical centres where they can receive comprehensive medical care. However, the sudden influx of a large number of casualties often exceeds the capacities of the closest hospital(s), making it impractical to provide treatment for all. Therefore, effective MCI management strategies, aiming at minimising mortality rates, necessitate crucial decision making regarding patient prioritisation and hospital selection (Larson et al., 2006; Shin and Lee, 2020). To establish and evaluate potential strategies, the dominant approach employed in literature is mathematical modelling (Lechtenberg et al., 2017), enabling the derivation of the optimal strategy.

An early study is presented by Sacco et al. (2005), exploring casualty prioritisation for transportation. Therein, the authors introduce the "Sacco Triage Method" (STM) and propose a mixed-integer programming model to optimise the transportation order for casualties exhibiting a deteriorating health status. The idea of deteriorating health status is adopted in the model presented by Dean and Nair (2014). Additionally, the authors acknowledge that the current health status of a casualty has an impact on the required treatment time in hospitals. By introducing the "Severity-Adjusted Victim Evacuation" (SAVE) model, the authors provide an extension to the model by Sacco et al. (2005) and incorporate the decision of hospital selection. Both models provide optimal solutions to allocation problems and outperform simplistic common heuristics and policies. However, a significant drawback of these models lies in their questionable practicality when applied to real life scenarios, as they require perfect information during the early stages of a disaster and substantial involvement from incident commanders (Mills et al., 2013; Dean and Nair, 2014; Mills, 2016). In response, more practical guidelines emphasise the utilisation of simple heuristics or "rules of thumb" (Dean and Nair, 2014). Considering the inherent stochastic nature of disasters, simulation emerges as a suitable method for evaluating newly developed policies and assessing their performance (Christie and Levary, 1998).

Several papers have evaluated patient prioritisation decision rules in the past. Jacobson et al. (2012) present a comprehensive model that represents casualties in MCIs as individual jobs, allowing for the examination of different prioritisation policies. Mills et al. (2013) propose a straightforward prioritisation policy using a fluid model to address casualty prioritisation under limited resources. Mills (2016) combines the advantages of mathematical modelling and simple policies by deriving propositions and heuristic policies. However, a drawback of the heuristics derived in the latter study is the availability of information, as obtaining a reliable estimate of the decrease in the survival function for each casualty class is often challenging.

Following the prioritisation of casualties, the subsequent challenge lies in their allocation to appropriate hospitals. In situations in which a substantial number of casualties necessitate medical care, a single hospital is often incapable to accommodate all cases. Consequently, the allocation of casualties to hospitals becomes a crucial decision. Wang et al. (2012) conduct an extensive study to evaluate multiple policies that require limited information. They examine twelve different hospital selection policies for casualties who have been triaged using the STM and categorised as either "general" or "specialised". The study's findings indicate that policies that reserve capacity for casualties in need of specialised facilities tend to outperform those that do not reserve such space. The study conducted by Jat and Rafique (2020) adopts a discrete-event simulation approach to evaluate the performance of different casualty allocation policies. Notably, they consider the coexistence of casualties originating from the disaster and routine patients visiting the hospitals, influencing the service capacities and waiting times. In contrast to the simulation developed by Jat and Rafique (2020), which primarily concentrates on hospital capacity and neglects ambulances as a potential bottleneck, Çağlayan and Satoglu (2022) focus on capacities at the disaster site. Their study aims to evaluate the impact of critical factors, such as available resources and prioritisation hospital selection policies, on the performance of casualty transportation systems. The overarching aim is to maximise the overall survival probabilities within these systems.

The concept of transporting casualties using mass transportation vehicles can be traced back to their utilisation during the First World War in France (Lamhaut et al., 2020). In more recent times, this concept has regained prominence, with practical implementations in France during the Covid-19 crisis to relocate patients between regions (Lamhaut et al., 2020, Dagron et al., 2022). Through the modification of high-speed train systems, sizeable numbers of casualties were efficiently conveyed across extensive distances, accompanied by a noticeable moderate demand for medical personnel (Dagron et al., 2022).

However, although some papers allow up to two casualties sharing an ambulance in the case of a demand surge in their models (Wang et al., 2012), to the best of our knowledge no model has incorporated multiple transportation methods. With transportation resources such as ambulances being scarce in MCIs, mass transportation vehicles could relieve ambulances by taking over longer sections, especially when casualties are transported to a more distant medical centre. With the newly freed up resources of ambulances, waiting times for the remaining patients could potentially be minimised. The aim of this study is therefore to evaluate the potential effect of including mass transportation vehicles and the impact on commonly used allocation practices.

3. Methodology

In order to evaluate the implications of including mass transportation vehicles, we construct a discrete-event simulation model. While the primary focus of the model is on patient transportation, the segmentation of transfers to the hospital for specific categories of casualties can also impact optimal casualty prioritisation strategies, making it essential to include them in our analysis too. The implementation and execution of the model are performed on a Python platform, utilising an Intel Core i7-1255U with a clock speed of 1.7 GHz and 16 GB of memory.

For our model, we assume that casualties arrive following a stochastic inter-arrival pattern, which can be represented by a time-dependent Poisson distribution. The severity of injuries varies among the casualties, leading to their allocation into one of three triage groups: "Immediate" if a casualty is life-threateningly injured, "Delayed" if a casualties is severely injured, or "Minor" for minor injured casualties. All casualties receive initial on-site treatment, during which their triage group allocation is reassessed. Those classified as "Immediate" or "Delayed" require additional treatment at a hospital and therefore need to be transported by an ambulance either to a hospital or a transfer point. At the onset of the disaster, ambulances and on-site treatment teams are assumed to be readily available, allocated proportionally based on the expected scale of each disaster site. Two types of hospitals are available: close hospitals, which can only be reached by ambulances, and remote hospitals, which can be accessed by both ambulances and mass transportation vehicles.

3.1. Process flow

Step 1 Casualties arrive at the triage zone at stochastic intervals, with the expected arrival rate decreasing as time elapses.

Step 2 Upon arrival, casualties are immediately registered and provided with initial first aid. Thereby first aid is limited to performing immediate life-saving measures such as stopping life-threatening bleeding, keeping the airway clear, and positioning patients (e.g., stable lateral position). Subsequently, each casualty is assessed using the "Sacco Triage Method" (STM), which assigns an RPM score based on the severity of their injuries (Sacco et al., 2005). The three components of the RPM score are the respiratory rate (per minute), the pulse rate (per minute) and the best motor response. The RPM score takes a value from zero to twelve, where zero is equivalent to a patient with life incompatible injuries. Based on this assessment, casualties are classified into one of the common triage categories: "Immediate", "Delayed", or "Minor".

With an RPM score less than five, they are assigned to triage category “Immediate”. Patients with a RPM score between five and eight are triaged as “Delayed” and all other patients are classified as “Minor”. Considering the minimal time required for triaging a patient (typically below one minute per patient, Heller et al., 2017), our model assumes the availability of ample resources and no delays at the triage station.

Step 3 Once triaged, casualties undergo on-site treatment to stabilise their condition. This treatment encompasses necessary medical procedures and interventions aimed at ensuring that casualties are in a safe and stable state for transportation. The treatment order follows an “immediate-first” policy based on the triage category. Following this policy causalities classified as “Immediate” are treated first until no casualty with this triage category is present. The same rule applies to “Delayed” casualties. After that the ones that are triaged as “Minor” are going to be treated. While receiving the on-site treatment, the casualty’s triage category is reassessed based on their updated RPM score. We assume that the RPM score decreases by one every two hours for casualties that are triaged as “Immediate” and “Delayed”. In the case of minor injuries, significant changes in their condition are not anticipated. However, initially, up to 10% of minor injuries may be misclassified, resulting in a deterioration of their condition over time.

Step 4 Casualties categorised as “Immediate” or “Delayed” are subsequently assigned to hospitals using one of the hospital selection algorithms (refer to Section 3.2). Unlike other models, such as the one proposed by Chang et al. (2023), hospital allocation is carried out prior to the availability of a transportation vehicle. This is because certain casualty prioritisation algorithms proposed in Section 3.3 take into account transportation time via ambulance when assessing the level of priority for each casualty. As a result, it is necessary for casualties to have already been allocated to a hospital before prioritising their transportation.

Step 5 After receiving on-site treatment, casualties with minor injuries are not considered further in this model, assuming that they can either leave the triage zone on their own or be evacuated using means of transport other than ambulances (following Wang et al., 2012).

Step 6 Casualties assigned to a hospital then await transportation via ambulance. Prior to commencing transportation, their RPM score is reevaluated to ensure appropriate transportation and prevent transporting deceased casualties.

Step 7 After completing the transportation of casualties to their first destination, whether it be a hospital or transfer point, the ambulance is released for redeployment.

Step 8 Upon arrival at the hospital, casualties receive further treatment as needed.

Step 9 In the case where a casualty’s initial destination is a transfer point, they will continue their journey utilising alternative means of transport, such as modified mass transportation vehicles, in order to be eventually transported to a hospital for subsequent treatment. For simplicity, we assume that mass transportation vehicles are available immediately and move directly to the destination transfer point. Moreover, we also assume that sufficient ambulances are already waiting at the destination transfer point, such that no additional waiting time is incurred.

Step 10 Once the casualties have been discharged from the ambulances, the vehicles are redirected to the disaster site for the purpose of transporting any remaining casualties, prioritising the cluster with the longest queue of casualties waiting for an ambulance.

Step 11 In the event that there are no casualties remaining to be transported, the ambulances return to their depot.

An overview of the processes is given in Figure 1 (following Shin and Lee, 2020 and Chang et al., 2023).

3.2. Hospital selection policy

For the hospital selection decision, we evaluate the commonly used “closest first” policy and compare it to an alternative selection policy, referred to as “distant-first”.

Under the traditional policy, the closest hospital with available capacity is chosen (Jat and Rafique, 2020, Chang et al., 2023). The proximity is determined based on the ambulance transport time from the disaster site to the hospital. If the hospital falls into the category of “close” hospitals or the casualty is classified as “Immediate”, the ambulance transports the casualty directly to that hospital. Otherwise, for “Delayed” casualties, they are transported to a transfer point.

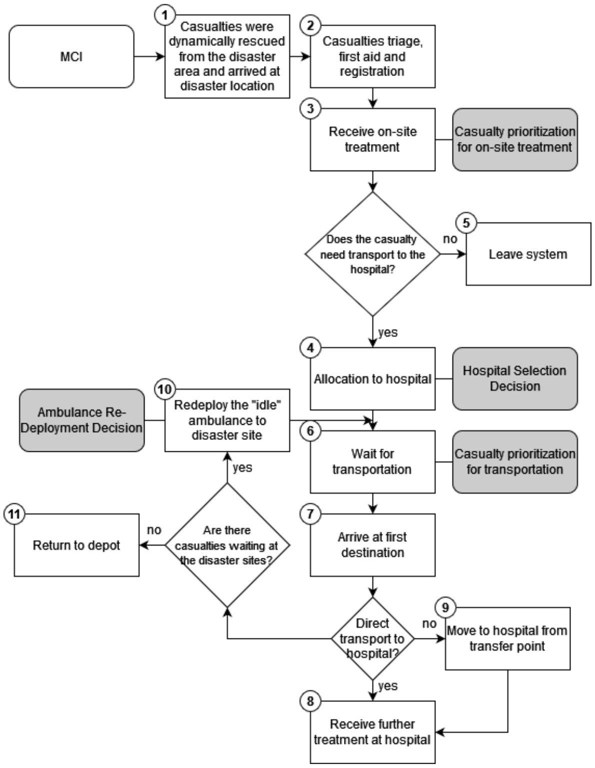

Figure 1. Process flow.

The alternative policy combines a hybrid approach for hospital selection. "Immediate" casualties are assigned to the closest hospital with available capacity, following the previous policy's ambulance travel time criteria. "Delayed" casualties, on the other hand, are allocated to the closest remote hospital, as they only require ambulances for transportation to the transfer point. The aim of this strategy is to minimise usage of ambulance resources to free them up for transporting other casualties, while also ensuring that capacities in local hospitals remain available for potential "Immediate" cases.

3.3. Casualty prioritisation for transportation

While the casualty prioritisation for on-site treatment follows an "immediate-first" strategy, different policies are evaluated for prioritising casualties for transportation. The original policy follows an "immediate-first" strategy, similar to the prioritisation for the on-site treatment. Within groups, casualties are selected for transportation following a first-in-first-out (FIFO) policy.

Alternative 1 employs a greedy strategy, known as the Shortest Processing Time (SPT), which prioritises casualties with the shortest section to be covered by ambulances. While the SPT strategy minimises overall completion time (Bruno et al., 1974), it can result in "Delayed" casualties being served before "Immediate" casualties. When multiple casualties have the same transportation time, priority is given to those with a longer remaining trajectory. If casualties have an equal remaining trajectory, a FIFO policy is applied. While this approach contradicts the commonly used policy of prioritising the most severely injured casualties, multiple studies have demonstrated that the widely employed "immediate-first" strategy may not always be optimal for maximising the survival rate among casualties (Shin and Lee, 2020).

Alternative 2 adopts a hybrid approach that combines the "immediate-first" and the SPT policy. The aim is to minimise overall waiting times by prioritising casualties with a shorter distance to be covered by ambulances. However, to avoid potential delays in transporting "Immediate" casualties, this policy alternates between the SPT and "immediate-first" approaches. Specifically, after selecting c_s casualties based on the SPT, the subsequent c_i casualties are chosen using the "immediate-first" strategy.

4. Experimental settings

For the case study, we consider a mass casualty incident in the city of Karlsruhe. Karlsruhe is located in the southwest of Germany, with a population of roughly 300,000 inhabitants (Statistisches Bundesamt, 2022b). We assume two main disaster sites: one disaster site in the area of the university campus east of the city centre, and a second disaster site in the area of the zoo in the south of the city centre. We estimate that 0.5% of the population are injured, resulting in roughly 750 casualties at each of the disaster zones. For the arrival pattern, we assume that approximately 40% of the casualties arrive within the first hour, 30% within the second hour, 20% within the third hour and 10% within the fourth hour. Of all casualties, around 20% are severely injured and categorised as "Immediate", 30% are moderately injured and categorised as "Delayed" and the remaining 50% are classified as "Minor" (Federal Office of Civil Protection and Disaster Assistance, 2017). Within each triage category, the RPM scores are assumed to be initially uniformly distributed. For on-site treatment, 22 teams are available at each of the disaster sites. Treating a casualty follows a Poisson distribution with a mean of 12 minutes, and truncated from five to 25 minutes (adapted from Ridler et al., 2022). To transport casualties, 21 ambulances are available (this corresponds to 25% of the ambulances based on Statistisches Bundesamt (2022c)

Scen. ID	HP	TP	Amb
1	HP_O	TP_O	normal
2	HP_O	TP_O	reduced
3	HP_1	TP_O	normal
4	HP_1	TP_O	reduced
5	HP_O	TP_1	normal
6	HP_O	TP_1	reduced
7	HP_1	TP_1	normal
8	HP_1	TP_1	reduced
9	HP_O	TP_2	normal
10	HP_O	TP_2	reduced
11	HP_1	TP_2	normal
12	HP_1	TP_2	reduced

Table 1. Factorial design.

multiplied by the proportional size of population for Karlsruhe), initially equally distributed among the disaster sites. Casualties can be brought to one of the five hospitals. Three of these hospitals are located in Karlsruhe, the remaining two are located in Heidelberg and Stuttgart. Casualties categorised as "Delayed" can be transported by ambulance or be transferred to a train at Karlsruhe Central Station to continue their transportation to one of the remote hospitals in Heidelberg and Stuttgart. For simplicity, the travel times are assumed to be deterministic. The travel times for ambulances are based on travel times provided by GoogleMaps©, the travel times for trains are based on the travel times for regional trains as reported on the DB Website. All travel times are increased by 10% to represent potential disruptions due to the disaster and additional five minutes are added for transferring the casualty into the vehicle and out of the vehicle (following Aringhieri et al., 2022). The hospital beds are based on the total number of beds per hospital (Statistisches Bundesamt, 2022d) multiplied by the average free capacity (Statistisches Bundesamt, 2022a, based on the value of 2019) and rounded down.

In the experimental design, we examine the influence of three distinct factors. The first factor focuses on the hospital selection policy, where we compare two different policies. The original policy (HP_O), also referred to as "closest first," is contrasted with the "distant first" policy (HP_1). The second factor focuses on the transportation order and involves the evaluation of three different policies. These include the original policy (TP_O) known as "immediate first", the policy that prioritises casualties with the shortest ambulance travel distance (TP_1 or "SPT"), and the "mixed" policy (TP_2 or "mixed") with $c_s = c_i = 1$. Additionally, we manipulate the number of available ambulances by reducing them by 25% to investigate the impact of different strategies when ambulances become a limiting factor. This leads to a total of twelve test settings as we explore all potential combinations. The specific combinations can be found in Table 1.

Given our assumption that no casualties are present at the disaster site initially, and the total number of casualties is capped at 1500, we have opted not to include a warm-up period in our simulation. Furthermore, a maximum run length has not been specified as the simulation terminates once all casualties have either been transported to the hospital or discharged following on-site treatment. To ensure a 95% confidence interval for the mean RPM score, we conducted 20 replications for each scenario. Although this threshold is typically achieved after five runs, we increased the number of replications to 20 to ensure the statistical significance of the results.

5. Results and analysis

Figure 2 illustrates the RPM scores per scenario, enabling a comparison of the effects of incorporating multi-modal transportation modes. The upper plot represents casualties categorised as "Delayed" and allocated to distant hospitals being transported by mass transportation vehicles, while the lower plot depicts the standard method of transporting all casualties by ambulances to their allocated hospital. The utilisation of multi-modal transportation to augment transportation capacities consistently yielded statistically significant improvements ($\alpha = 0.05$) in all scenarios, with the exception of Scenario 2 where no statistically significant difference was found. However, a remarkable observation arises when comparing the relative performance of different policies within each setting. In the traditional setting, where only ambulances are employed, allocating casualties to the closest hospital emerges as a seemingly effective strategy. Surprisingly, this approach does not seem to be optimal when multi-modal transportation modes are introduced. Therefore, in the subsequent sections, our focus shifts towards identifying the optimal policies when incorporating mass transportation vehicles.

5.1. Comparison of different policies and survival analysis

In order to examine the potential differences in outcomes resulting from the various policies, we conducted pairwise t-tests.[1] The results yielded several important observations. First, there was no statistically significant difference in means observed between Scenario 3, 4, 7, 8, and 11, 12. This indicates that when implementing a "distant-first" policy, independent from the prioritisation policy even a 25% reduction in ambulances does not significantly impact the mean RPM score. Conversely, a reduction in available ambulances

[1] We conducted a Shapiro test with a significance level of $\alpha = 0.05$ to ensure that the conditions for normally distributed values were met.

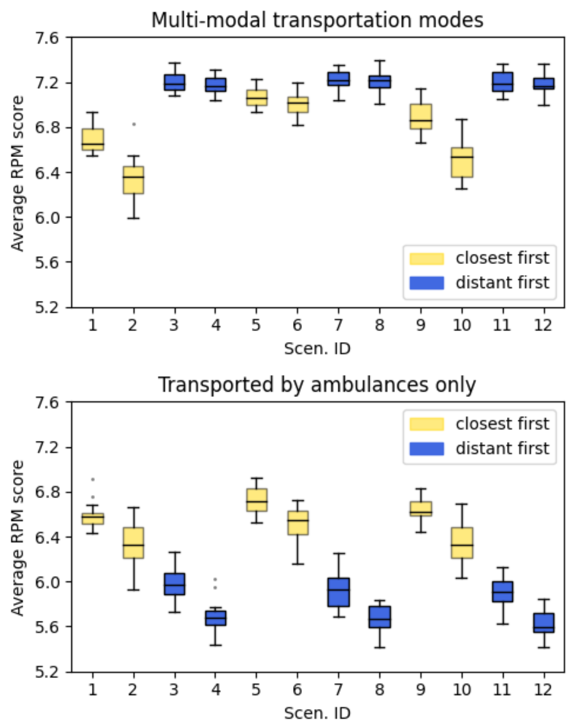

Figure 2. RPM score per scenario with and without additional transportation modes.

resulted in a statistically significant decrease in the RPM score for scenarios implementing the "closest-first" policy. Comparing the hospital allocation policies, the "distant-first" policy outperformed the "closest-first" policy in terms of RPM scores, with statistical support. Among the scenarios where the "closest-first" policy is implemented, the SPT policy exhibited the highest performance, followed by the "mixed" policy, while the "immediate-first" policy performed the poorest.

The findings from the survival analysis, as illustrated in Figure 3, provide additional support to the observations derived from the RPM score analysis, indicating that adopting a "closest-first" policy leads to increased mortality rates.

As the scenarios with even numbers share the same parameters as the odd-numbered scenarios but with limited resources, specifically ambulances, our analysis will now solely concentrate on the odd-numbered scenarios. Moreover, our further analysis will focus the scenario with the lowest performance (incidentally employing the most intuitive policies), Scenario 1, with the scenario attaining the highest median RPM score, Scenario 7. However, it is important to note that no statistically significant difference was found through pairwise t-tests when comparing Scenario 3, 7, and 11.

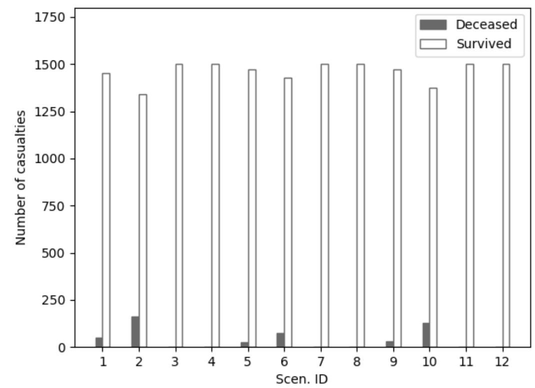

Figure 3. Number of surviving and deceased casualties per scenario.

The Tables 2 and 3 provide an overview of the category transitions during the simulation. The columns represent the initial categories assigned to the casualties, while the rows represent the final categories. Initially, approximately 50% of the total casualties are classified as "Minor", 30% as "Delayed", and 20% as "Immediate". We refer to Section 4 for more details. According to the assumptions, around 10% of the casualties initially classified as "Minor" may undergo a category change. Since on-site treatment follows an "immediate-first" strategy, the reassessment of category may occur relatively late, resulting in these reclassified casualties frequently being labelled as "Immediate".

To / From	Imm.	Delay.	Minor	Tot.
Deceased	0.63	2.70	0.00	3.33
Immediate	19.24	6.84	5.18	31.26
Delayed	0.00	20.19	0.07	20.26
Minor	0.00	0.00	45.15	45.15
Total	19.87	29.73	50.40	100.00

Table 2. Change in triage categories (%), Scen. 1.

To / From	Imm.	Delay.	Minor	Tot.
Deceased	0.00	0.00	0.00	0.00
Immediate	19.65	0.01	5.01	24.67
Delayed	0.00	30.18	0.00	30.18
Minor	0.00	0.00	45.15	45.15
Total	19.65	30.19	50.16	100.00

Table 3. Change in triage categories (%), Scen. 7.

A closer examination of the "Delayed" casualties reveals that in Scenario 1, around one third of them experience a worsening in their category, with an average fatality rate of approximately one casualty out of every eleven cases. Conversely, Scenario 7 demonstrates minimal deterioration among "Delayed" casualties. Turning to "Immediate" casualties, Scenario 7 records no fatalities, while Scenario 1 registers a small number of casualties who do not survive.

5.2. Ambulance queues and time spent in the system

Figure 4 provides a visual representation of the queue length over time for Disaster Site 1. Notably, while in Scenario 7, the queue remains consistently low with only a small number of casualties awaiting transportation, a long queue of almost 70 casualties is built up in Scenario 1. The abrupt surge in Scenario 1 can be explained by the policy of initially allocating all casualties to the nearest hospitals. Once these hospitals reach their capacity, casualties must be transported to more distant hospitals. Consequently, "Delayed" casualties arriving later face prolonged waiting times as "Immediate" casualties are also being transported to more remote hospitals by ambulance. This increases the likelihood of a deterioration in their health status, leading to their reclassification as "Immediate" cases. Once reclassified, they are assumed to be fully transported by ambulance, further delaying transportation for subsequent casualties.

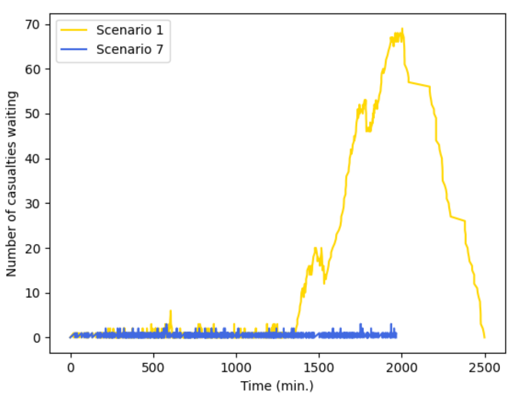

Figure 4. Queue length for ambulance transportation of Scenario 1 and 7.

The insights obtained from Figure 4 are further supported by the results depicted in Figure 5. In Scenario 7, in which the "distant-first" policy is implemented, the majority of casualties experience waiting times of less than 15 minutes for an ambulance. In contrast, when transporting casualties to the closest hospital as in Scenario 1, waiting times frequently exceed one hour. As expected, the SPT policy yields the shorter waiting times than the "mixed" and "immediate-first" policy when long queues build up. These variations have direct implications on the average RPM (Figure 2) and the number of survivors (Figure 3).

The time spent in the system is significantly impacted by the waiting time for the ambulance, resulting in a distribution similar to that depicted in Figure 5.

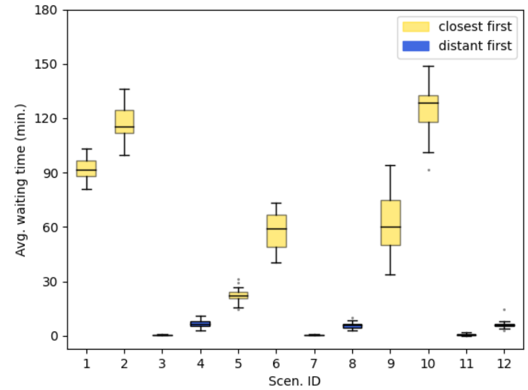

Figure 5. Avg. waiting time for ambulance transportation.

When analysing the time spent in the system based on the initial categories, the influence of the transportation policy becomes apparent. A notable contrast can be observed between Scenario 1 and 5, wherein Scenario 1 prioritises "Immediate" casualties (highlighted in red), while Scenario 5 prioritises casualties with a shorter path covered by ambulances, which primarily consists of "Delayed" casualties (highlighted in orange).

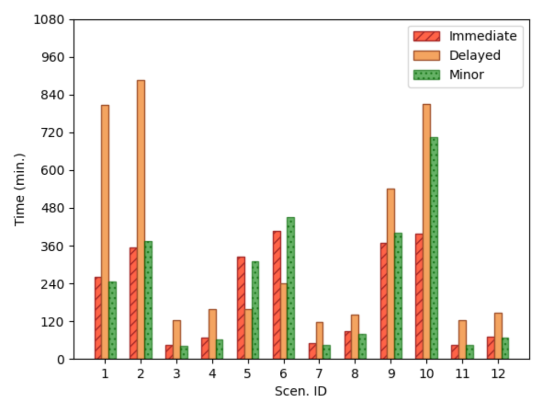

Figure 6. Max. time in system per initial triage category (avg. values).

In addition to evaluating the maximum time spent in the system, the maximum completion time emerges as a vital measurement. However, given the stochastic nature of casualty arrivals, this metric is inherently influenced by the arrival timing of the last casualty. Therefore, although the results show some variation based on the

Scenario	Immediate	Delayed	Minor
1	2,183.45	2,704.15	2,194.15
2	2,263.60	2,792.80	2,268.65
3	2,032.45	2,113.35	2,039.00
4	2,049.40	2,144.25	2,060.30
5	2,193.75	2,116.65	2,226.55
6	2,321.75	2,128.30	2,313.30
7	2,027.05	2,117.95	2,035.70
8	2,036.60	2,117.00	2,043.90
9	2,347.40	2,500.00	2,327.70
10	2,605.00	2,759.40	2,111.45
11	2,036.75	2,125.90	2,047.00
12	2,031.55	2,123.90	2,045.70

Table 4. Max. completion time per triage category (avg. values).

different scenarios, they are comparably more balanced when compared to the maximum time spent in the system.

6. Conclusion

In this work, we have built a discrete-event simulation to assess the efficacy of various transportation policies for evacuating casualties to hospitals during an MCI. Our findings indicate that the inclusion of mass transportation vehicles can significantly enhance survival rates, even under limited ambulance capacity. These results are also in line with the observations made during the actual transportation of casualties via trains in France. Notably, traditional intuitive strategies, such as transporting casualties to the nearest hospital, were outperformed by nonintuitive approaches, such as transporting certain casualties to more distant hospitals. Furthermore, incorporating established machine scheduling policies, such as prioritising casualties with shorter ambulance request times, within a "closest-first" framework led to additional improvements. In order to account for fairness considerations, we also propose a "mixed" policy that strikes a balance between waiting times and urgency.

Although this simulation extends the current literature, the study does have some limitations. The first limitation pertains to the simplified assumption regarding the transportation of "Delayed" casualties. In this simulation, we assumed that "Delayed" casualties immediately continue their journey using one of the available transportation vehicles upon reaching the transfer point. However, in reality, this assumption may not hold. Future research could explore the impact of transportation vehicle availability, including mass transportation options, as well as optimal batch sizes, to optimise casualty transportation metrics as presented above. In addition, the simulation neglects the consideration of waiting times at hospitals. As a result potential benefits of distributing casualties among multiple hospitals to balance the patient load are not accounted for. Future research could examine simultaneous load balancing strategies to minimise waiting times and optimise the commencement of actual treatments (Jat and Rafique, 2020).

Nonetheless, incorporating these modes of transportation introduces novel complexities and opens further research directions. In addition to medical considerations such as the criteria for selecting eligible casualties, coordination between providers of different transfer modes plays a crucial role (Dagron et al., 2022). Therefore, in future research, we aim to extend the research by dropping the currently simplified assumptions associated with mass transportation vehicles of immediate availability. Additionally, we aim to incorporate multiple modes of transport with various characteristics to assess the effectiveness of each mode. Furthermore, to examine the model's robustness, we plan to apply it to instances from various regions.

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