

**SIMEDIS 2.0 : ON THE ROAD TOWARD A COMPREHENSIVE MASS CASUALTY INCIDENT  
MEDICAL MANAGEMENT SIMULATOR**

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**ABSTRACT**

Mass casualty incidents still cause a huge amount of deaths and injuries in the 21<sup>st</sup> century. Research on these events is challenging due to inherent ethical and logistical difficulties. Computer simulation models can overcome these difficulties, and offer evidence on which to base policy and decisions. In this paper a discrete event simulation model is described, designed to analyze prehospital policies and commonly made decisions. We studied an airplane crash scenario and analyzed mortality as a primary and treatment and transport times as secondary outcome measures. We implemented resource dispatching, search and rescue at the disaster site, triage, treatment and evacuation of victims to healthcare facilities. Overall we conclude that for this particular scenario - where treatment capacity is sufficient - the best outcome for victims can be achieved by the combination of triage, pre-triage and quick distribution of victims to regional hospitals.

**1 INTRODUCTION**

A mass casualty incident (MCI) is an event that overwhelms the response capacity of the local healthcare system for a certain period of time (Debacker et al. 2012). The goal of disaster medical management strives to minimize as much as possible the loss of life and the suffering of the affected population by managing this temporary imbalance between the immediate health needs and the actual response capacity (Hubloue and Debacker 2010). Successful response to an MCI depends on effective and efficient setting of organizational and medical priorities in order to relocate and optimize the utilization of the available resources, and to mobilize additional assets (Lennquist 2012).

To date, there is no evidence-based literature that clearly defines the best medical response principles, concepts, structure and processes in a disaster setting (Bradt 2009) Much of what is known about disaster medical management results from descriptive studies and expert opinion (Straton 2014). An evidence-based approach through prospective randomized controlled studies of the effectiveness of medical and

operational interventions in response to an MCI is impossible and ethically inappropriate. However, computer simulation can provide evidence-based data for an optimal use of resources when applying specific response interventions and procedures, taking into account the contextual factors of the affected area and the specific disaster scenario (Hubloue and Debacker 2010).

Computer simulation modeling has been successfully used in non-medical contexts to analyze complex interactions and is increasingly recognized as a valid technique to analyze and optimize emergency medical management (Laker et al. 2017). Because of the complexity involved, modeling and simulation are often limited to certain subprocesses of the MCI medical management such as transportation or allocation of casualties to hospitals (Timbie et al. 2013).

In this paper we describe a comprehensive MCI medical management simulator incorporating search and rescue, on-site triage and treatment of casualties, their evacuation and admission to the emergency department of healthcare facilities, based on previous work (Debacker et al. 2016; Van Utterbeeck et al. 2011; Ullrich et al. 2013). The objective of this project is to analyze and test the effect of MCI medical management policies and procedures in order to identify the optimal response strategies for various MCI scenarios.

The remainder of the paper is organized as follows. Section 2 provides a description of the simulation model, incorporating 3 interacting components and the added improvements. In section 3 a hypothetical MCI scenario is defined to which SIMEDIS 2.0 is applied to determine the best management practice for this particular MCI. In section 5 results of the experiments performed are presented and discussed, including some limitations. Finally, section 6 concludes the paper and offers suggestions for future work.

## **2 SIMULATION MODEL**

Since the main aim of a disaster medical response (DMR) is to minimize as much as possible the mortality and morbidity of the survivors, a victim-centered simulation tool was developed in which the casualties drive the simulation through triggering the various processes at defined service environments within the medical assistance chain. Our goal was not an attempt to develop a simulation tool that can be used as a decision support system in real time, but rather a tool to test interventions included in disaster plans as well as alternative assumptions in order to achieve best practice.

The conceptual SIMEDIS simulation model is presented in figure 1. It consists of three interacting components: the victim manager module - where the health state of each victim is monitored-, the resource manager module - that tracks resource utilization - and the medical response module - where the victims interact with the environment and the resources at the disposal of the healthcare responders.

The working principle of the simulation model is discrete event simulation. This principle was chosen because all of the considered events are discrete events, e.g. the arrival of resources or the start of treatment, or can be modeled as such, which is the case for the evolution of the victims' health conditions (Van Utterbeeck et al. 2011). The previous simulation model was implemented in Arena<sup>®</sup> (Kelton et al. 2002) and included many hard-coded variables (Debacker et al. 2016). In order to create a more general model, where the scenario with its procedures and parameters can more easily be adjusted, the model has been re-implemented from scratch in the Julia language (Bezanson et al. 2017), using the SimJulia package (Lauwens 2017). Moreover, this package results in significantly reduced simulation runtime.

The service environments in the simulation in the medical response model represent the spaces through which the victims flow in the MCI medical response chain: the disaster site, the casualty collection point (CCP), the forward medical post (FMP), the non-urgent care area (NUCA), the healthcare facilities (HCF), the non-urgent care facilities (NUCF), and ambulances. The NUCA and NUCF are not yet implemented in the simulation model. The processes included in the medical response model represent the interventions which are required to manage the casualties: preliminary triage, field triage, treatment, distribution, evacuation and definitive care of the injured survivors. The resources represent the assets (people, equipment, supplies, transportation means) required to carry out the processes.

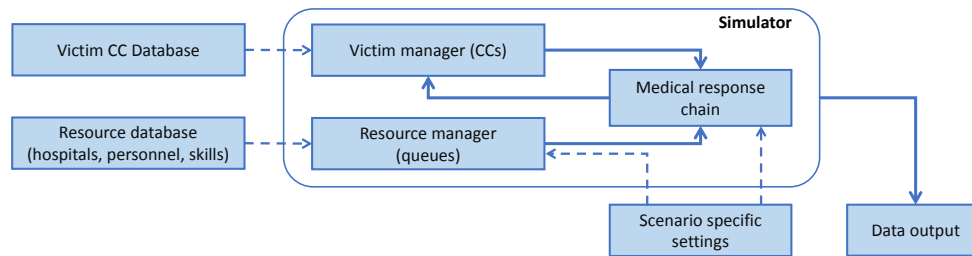


Figure 1: An abstracted overview of the components of the simulator. Dashed arrows represent initialization of parameters and objects at simulation start.

The specificity of the SIMEDIS simulation model is the fact that the victim entities evolve in parallel through both the victim monitoring model and the medical response model. The interaction between both models is ensured through triggers, i.e. a time trigger and a medical intervention or treatment trigger. At each zone of interest, a triage must be performed together with a decision on the disposition of the victims regarding treatment and/or evacuation. For the treatment and evacuation tasks required for a given victim a strict order exists in which they are performed based on a priority (or triage) code assigned to the victim and on the availability of resources at the zone of interest. A detailed description of the victim model and the three interacting components can be found in (Debacker et al. 2016).

## 2.1 Victims

The victim model consists of victim profiles and a set of transitions to move from one clinical condition to another. Victim profiles are composed of detailed information about victim features that do not change over time (age, gender, anthropometric data, type of injury, diagnosis) and a set of changing clinical parameters representing the victims current state, called clinical conditions. Transitions between these clinical conditions will occur after a certain period of time has elapsed or after the administration of a treatment. A detailed description of the modeling of the clinical conditions and the transitions between can be found in Van Utterbeeck et al. (2011) and a conceptual representation is provided in the bottom half of figure 2. The exact values of the clinical condition parameters and the transitions are determined by subject matter experts (SMEs), as well as the required hospital capabilities to treat the victims such as trauma center, neurosurgery or pediatric intensive care unit (ICU).

## 2.2 Processes

After the simulation starts, the victims are generated at the disaster site where they self-evacuate or are rescued by firefighters. They are collected and transported to the Casualty Collection Point (CCP), where they are triaged. Triage is a process used to determine the order of medical or logistical interventions that are performed on victims, from life-saving medical interventions to transport to a Forward Medical Post (FMP), stabilizing medical interventions and transport to the hospital. Triage is a dynamic process, that needs frequent repeating along the evacuation chain to achieve optimal delivery of care. In our simulator we included the options of preliminary triage, field triage and emergency department (ED) triage. Preliminary triage is used to determine evacuation order to the CCP; field triage is used to determine the treatment and evacuation order at the FMP and ED triage is used to determine treatment order in the ED. The exact implementations are further explained in section 3.

The treatment and transport aspects of emergency medical response can be organized according to one of two possible policies: Scoop and Run (S&R) and Stay and Play (S&P). S&R is bringing the victim to a hospital as quickly as possible, providing the necessary treatment in the ambulance. Reasons to pick this policy include safety issues at the incident site or a high treatment and surge capacity of the surrounding hospitals. S&P is stabilizing victims before transport to the hospital. The main reason to choose S&P is

when long transport times are expected, for example due to a low treatment capacity in the surrounding hospitals, necessitating transport of victims to hospitals further away, or long distance to the closest hospital. The victims will receive stabilizing interventions in an improvised field clinic called the Forward Medical Post (FMP). As soon as the FMP is operational, victim transport from the CCP to the FMP commences. At the FMP the victims are triaged again, and treated in the established triage-order. In this updated version of the simulation model we have added an intermediate policy between S&P and S&R based on the S&P strategy which we call Stay and Play and Run (S&PR). In this policy, every time a victim arrives when there are no available healthcare providers for treatment, the simulation model checks if there is an available ambulance, supervisor and hospital for transport. If all required conditions are fulfilled, the victim bypasses the FMP and gets sent to the appropriate hospital, similar to S&R.

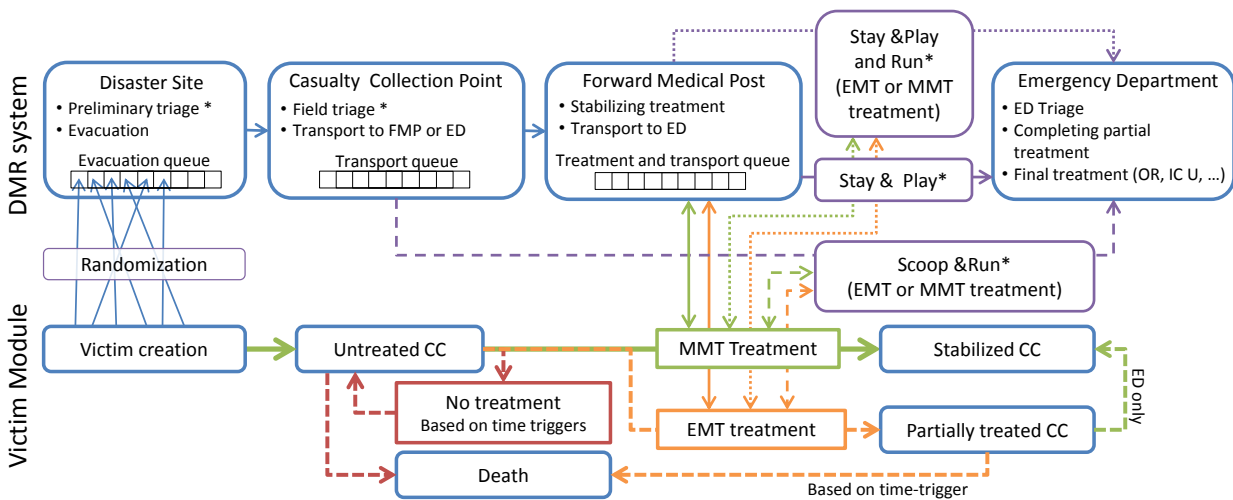


Figure 2: An abstracted overview of the environments in which the victims can reside, and the main processes they undergo at each location. The bottom half of the image represents the clinical condition model of the victims. The different evacuation (and corresponding treatment) policies are represented by solid lines for S&P, dashed lines for S&P and dotted lines for S&PR. Processes marked by an asterisk signify optional parameters.

Depending on the chosen policy, the victims are transported to the optimal HCF directly from the CCP or after receiving stabilizing treatment in the FMP. The optimal HCF is based on the victim’s injury severity and medical and ranges from a trauma center to a non-urgent healthcare facility. When multiple hospitals fulfill the requirements, two methods of hospital selection can be used: ‘Round Robin’ and ‘Closest First’. In ‘Round Robin’ mode, each subsequent victim is transported to the next available hospital (in ascending order of driving time). In ‘Closest First’ mode, the victim is sent to the closest suitable treatment facility with an available bed.

An overview of the different processes, the relations between them, the flow of victims from one process to the next, and the interplay between the victims’ clinical conditions and the treatment processes is given in figure 2.

### 2.3 Resources

The Belgian Emergency Medical Services (EMS) system consists of three skill levels: basic life support ambulances with 2 EMTs, paramedic intervention teams (PIT) with 1 EMT and 1 emergency nurse, and mobile medical teams (MMT) with 1 emergency physician and 1 emergency nurse. In case of a MCI, health care is first provided by local EMS and Red Cross rapid intervention teams and additional support is dispatched to the scene from neighboring regions according to the health needs assessment. Hospitals

included in the EMS system will increase the treatment capacity by activating their hospital emergency incident management plan.

In the current model all ambulances are equivalent. The ambulances are completely restocked after delivery of a victim to a hospital. Ambulances are dispatched with 2 EMTs and can transport 1 supine victim and 2 additional sitting people, not including the 2 EMTs.

Hospitals are the current endpoint in our simulation model. A hospital has an emergency department with a legally defined surge capacity, as well as a variable treatment capacity depending on the current ED, operating theater, ICU and ward bed occupancy. When the signal is given, the hospitals scramble to augment this capacity to their required surge capacity.

## **2.4 Implementation**

When a victim arrives at a new location, the program checks whether the required resources are available. If so, these resources are seized. If not, the victim is placed in the queue of the specific location according to the queuing discipline. When a resource arrives at a location or is released, the program checks whether any of the victims in the queue can now be processed. After completing the process, the victim is transferred to the next step. The logic for the transport process is the most complicated. Here, victims with different triage categories may require supervision by different medical personnel. Furthermore, victims may require a specific hospital capability.

Every time a victim evolves to a new clinical condition the model checks for possible time-triggered transitions. If such a transition is found, it is scheduled to take place after the specified time interval, with a stochastic variation. If treatment is initiated before the time-triggered transition occurs, the latter is canceled. For many clinical conditions multiple treatments are possible, where the more advanced treatment containing more interventions can usually only be performed by the more highly trained medical personnel.

In order to simulate the chaos inherent to a MCI scene a stochastic variation is applied to the event times. For the search and rescue intervals a normal distribution is used which is cut off at 75% and 125% of the expected value. The travel times are modeled using a lognormal distribution cut off at 80% and 200% of the expected value. For all other time intervals a triangular distribution is used with endpoints 20% above and below the expected value.

## **3 SCENARIO**

The MCI scenario being simulated consists of an airplane crash during an emergency landing at an international airport, in normal weather conditions. The plane is carrying 250 passengers, of which 205 are injured at impact. Severity distribution of victims and operational parameters are explained in detail in (Debacker et al. 2016). Directly after the plane crash, able-bodied victims leave the airplane on foot using the emergency exit slides and are collected by the first-responder firefighters in a casualty collection point (CCP). It is assumed that victims who are able to self-evacuate do not have potentially life-threatening injuries. They are therefore evacuated separately to a NUCA. Although it is important to give care and attention to all victims in a real situation, the procedures regarding the non-urgent victims are not simulated in detail, since this would not affect the outcomes of interest. Search and rescue of the remaining victims by the firefighters starts 5 minutes after the crash.

The search and rescue is modeled as a stochastic arrival process of victims at the CCP. Three different rescue rates are possible, which increase after 26 minutes after the crash when additional evacuation exits are cut out in the plane's fuselage. Firefighters evacuate the victims in random order or in the order determined by the preliminary triage (pre-triage).

Ambulances and MMTs are dispatched from their current location and arrive based on real life activation times with a stochastic variation (Ingolfsson 2013). One MMT assumes the role of medical director. The MMT from the airport is assigned the task to triage urgent victims at the CCP. The second MMT arriving at the scene will also be assigned to assist with field triage. In case pre-triage is enabled this MMT will

perform pre-triage of the victims who have not yet been rescued from the plane. All other MMTs will be assigned to construct the FMP and treat victims, as well as to supervise transport. When all victims have been triaged, the Airport MMT will start to triage and treat the non-urgent victims, while the other triage MMT will be sent to the FMP to treat and supervise the transport of the urgent victims. When the S&P policy is chosen, the first 5 ambulances arriving at the scene will transport victims from the CCP to the FMP, while the other ambulances are used to transport victims from the FMP to the hospital.

Field triage is implemented using NATO triage categories, which range from T1 to T4. T1 victims have life-threatening injuries and should be treated within one hour. T2 victims are also seriously injured, but their health is estimated to remain stable for 2-6 hours after which their condition becomes unstable. Both T1 and T2 victims should be transported to a hospital. T3 victims have no life-threatening injuries, can walk and do not require hospitalization. T4 victims are similar to T1 victims, however there are not enough resources available to provide possibly life-saving care (Nato Standardization office 2015). A further differentiation is provided by using the RPM score, which evaluates the victim's Respiratory rate, Pulse, and Motor response (Sacco et al. 2005). The triage result is used to decide in which order the victims leave the CCP. If there are victims with the same triage and RPM score, a first-in-first-out principle is used as a tie breaker. Victim treatment and transport order are determined by the same procedure. Since it is assumed that triage occurs at a specific moment, the order of each queue is not updated due to time-triggered transitions.

In S&R mode, victims are collected at the CCP, triaged and transported to the hospital. The MMTs limit themselves to triaging victims, assigning a hospital based on the victim's needs and treating victims in the ambulance. A pre-transport immobilization of fractures and victims with suspected spinal injury was added, due to the relative impracticality of these acts in a driving ambulance. In S&P mode, victims are transported to the FMP. For the current scenario we assume that the required resources for treatment and stabilization (such as stretchers, oxygen and medical supplies) are sufficient for the number of victims. When a victim arrives at the FMP the program checks if there is medical personnel available to treat the victim. A T1 victim requires a physician and nurse, while T2 victims can be treated by either a physician or a nurse. When there is not enough personnel available, the victim is placed in a queue ordered by triage category, RPM score, and arrival time. After stabilization, they are transported to a hospital.

Five different supervision settings for transport of the victims to hospitals have been defined. When the 'Low' setting is selected, victims are supervised by EMTs only. In the 'Medium' setting, T1 victims require a nurse or physician and the T2 victims require only an EMT. In the 'Normal' setting, T1 victims require a nurse or physician and T2 victims require a nurse. In the 'High' setting, T1 victims require an MMT for transport and T2 victims require a nurse. In the 'Flexible' setting, T1 victims are supervised by either a physician, nurse or EMT, and T2 victims by a nurse or EMT. For all cases with multiple supervision options, they are listed in order of preference.

#### **4 METHODOLOGY**

The main outcome in this simulation experiment is number of deaths, referred to as mortality. Mortality is a clinically significant endpoint when reporting disasters, is easily (objectively) measured, and is straightforward to compare across simulations. Mortality was analyzed by means of ANOVA, to identify the effect of the various parameters. Because providing the best outcome is difficult to measure directly in the simulation model, medical response performance indicators were used as a proxy measure for morbidity. The two primary performance indicators analyzed are the waiting time before receiving the first stabilizing treatment and until arrival at the hospital. The Time To Treatment (TTT) and the Time To Hospital (TTH) are defined as the time between the injury and the start of treatment and arrival at the hospital respectively. A distinction is made between T1 and T2 victims due to different expected survival times. For these time indicators the mean and maximum are analyzed using ANOVA. The mean time provides information about the average performance, whereas the maximal time represents the total duration of the different processes in the medical MCI response chain.

For each replication, the results are verified by internal checksums (checking for missing victims, seeking impossible admissions and checking that all resources are accounted for). Furthermore, unit tests were created to check individual aspects of the simulation model. In addition, tracing of the victims through log files of individual replications was performed to identify problems and to verify the correctness of the simulation. Finally, a sensitivity analysis was performed on the number of replications, in order to identify the smallest number of simulations needed to achieve a stable solution. We determined this to be 35 replications per parameter set. At this number the 95% confidence interval halfwidth for each set is maximal 1.02 deaths.

## 5 RESULTS AND DISCUSSION

### 5.1 Mortality

The minimum mortality observed in a single simulation run is 4, the maximum is 34 and the average is 19.01. In this section the effects of the various parameters on the total mortality are reported. In order to assess the effects of each individual parameter on victim mortality, we assessed both statistical significance and the actual difference in the mortality. Statistical significance was determined by a one-way ANOVA of the mean differences for each parameter. The difference between the highest mean mortality and the lowest mean mortality was calculated across all parameter settings. This is represented in table 1 as the maximal means difference. This table shows that the largest effect of a single parameter on mean mortality is found for field triage. The effect of the supervision level is presented for the three policies, since the found effect is much larger for S&R than for the other two policies.

Table 1: Results of the analysis of the mean mortality for each parameter setting.

Parameter	P-value	Max. Mean Difference	Lowest Mean Mortality
Policy	$\ll 0.01$	1.68	S&PR
Preliminary triage	$\ll 0.01$	3.15	Yes
Rescue rate	$\ll 0.01$	1.11	Fast
Field triage	$\ll 0.01$	6.05	Yes
Arrival resources	$\ll 0.01$	0.36	High
Transport supervision	$\ll 0.01$	4.55	Flexible
Transport supervision S&R	$\ll 0.01$	10.94	Medium
Transport Supervision S&P	$\ll 0.01$	0.46	Low
Transport Supervision S&PR	$\ll 0.01$	3.07	Low
Distribution over hospitals	$\ll 0.01$	0.15	Closest First
Distribution over hospitals S&R	$\ll 0.01$	0.40	Closest First
Initial hospital capacity	0.49	0.04	High

In figure 3 the average mortality for different parameter sets is shown. The results show that for the S&R policy, a high supervision level leads to worse results than the other supervision levels. We therefore performed a subgroup analysis per supervision level. This reveals that for the S&R policy the mean mortality difference between the three policies would be larger than shown in table 1 if the supervision level 'High' was not considered. This can be explained by the fact that for this setting T1 victims require supervision of both a nurse and a physician, thus greatly reducing the effective transport capacity.

The results indicate an association between field triage, preliminary triage and rescue rate. When field triage is present, higher rescue rates lead to a decrease in mortality, and pre-triage seems to reduce the effect of the rescue rate on mortality. When field triage and pre-triage are not performed, then the rescue rate does not seem to have a notable effect on mortality. However, when there is no field triage, but only a preliminary triage, lower rescue rates result in lower mortality. This is because in lower rescue rate

scenarios fewer victims are evacuated without any form of triage before pre-triage starts. Therefore, more victims will arrive at the CCP and/or FMP ordered by the severity of their conditions.

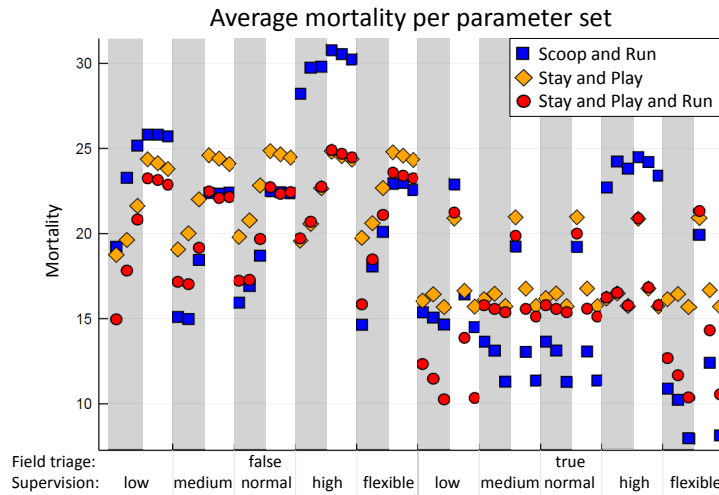


Figure 3: Average mortality for the different parameter sets from table 1. The grey bars represent scenarios where pre-triage is present as opposed to the white bars where it is absent. On the smallest level, the data points are grouped in sets of three, corresponding to the low, medium, and high rescue rates respectively.

After determining the statistical significance of the differences between the options for the various parameters, we address the question of which options result in the lowest mortality. We used two approaches to answer this question. The first strategy is to examine the average mortality across all simulations with the specific parameter of interest. However, a closer look at figure 3 shows that some parameters interact with regard to mortality. While the S&PR policy has the lowest average mortality, the S&R policy is the one that provides the lowest mortality of all simulation runs. This can be explained by both policies having different interaction effects with the supervision level. The S&R policy is very susceptible to the supervision level, resulting in a worse average due to the very high mortality for the supervision setting 'High'. The S&PR policy is less sensitive to differences in supervision level, as can be seen in figure 3. Therefore, this policy has less extreme results and a better average.

## 5.2 Time Intervals Before First Treatment and Hospital Arrivals

For each parameter set, the average values of the mean and maximum TTT and TTH were calculated for the T1 and T2 victims separately. The results are shown in figure 4. On average it takes 66 minutes before the treatment of the last T1 victim commences, which is just above the one hour guideline. T2 victims receive treatment within 162 minutes on average, which is well within the range of 2-6 hours. In 72 out of 151200 simulation runs all T1 victims die before receiving treatment, resulting in a TTT and a TTH of 0. These replications have been removed from the analysis.

ANOVA analysis of the results show that many means differ by less than 5 minutes when the various options for a single parameter are compared. Although most of these differences are statistically significant, only differences of more than 5% of the means are considered to be possibly clinically relevant. The results are presented in table 2. When interpreting these results it is important to keep in mind the results of the mortality analysis. For example, no preliminary triage often results in lower average TTT and TTH. However, this might be caused by the higher mortality which results in less victims to be treated or transported. On the other hand, the result that the Closest First distribution results in shorter TTHs is in line with the expectations.



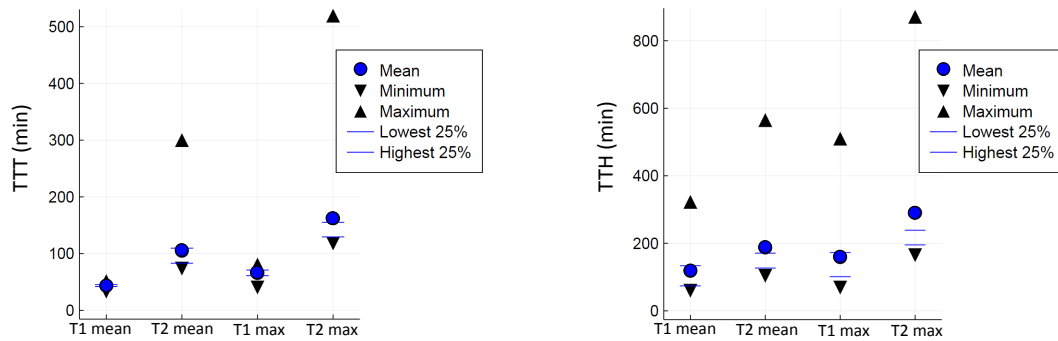


Figure 4: Overview of variation in TTT and TTH averages for each parameter set. Solid circles correspond to the mean of all runs, blue lines show the lowest and highest 25%, and triangles indicate the most extreme values.

The largest differences are found for the various policies and supervision level. For the TTT, S&R results in shorter times for T1 victims, whereas for T2 victims S&PR leads to the best results. As expected, S&R results in much shorter TTHs than S&P and S&PR. The effect of supervision level on TTT is not relevant for the levels 'Low', 'Medium', 'Normal', and 'Flexible'. For these levels the differences between the averages are all less than 2 minutes. However, the 'High' supervision level results in longer waiting times, since this setting greatly reduces the transport capacity of T1 victims. For T1 victims, the 'Low' and 'Flexible' supervision levels result in the shortest TTH with a mean of 87 minutes and maximum of 119 minutes on average. The TTHs of the 'Medium' and 'Normal' levels differ only by 1 minute, but are about 30 minutes longer than the 'Low' and 'Flexible' levels. For the T2 victims, the average TTH of the 'Low', 'Medium', 'Normal', and 'Flexible' supervision levels shows a maximal difference of 4 minutes with a average TTH of 137 minutes and a maximal TTH of 204 minutes. The TTH of T2 victims transported with a 'High' supervision level is twice the time of the best option, i.e. a 'Normal' supervision level.

### 5.3 Limitations

A first limitation of the current model is the lack of evidence based empirical data concerning the change in the clinical condition of the MCI victims, hence the reliance on subject matter experts. A second limitation is the assumption that triage and treatment are always executed flawlessly. Therefore the simulation model's quantitative outcomes should be interpreted with caution. However, the simulation model's qualitative results can help to understand relationships between the different aspects of the medical management of MCIs and help guide policy and strategy decisions.

## 6 CONCLUSION

This paper discusses the progress toward a comprehensive MCI medical management simulator. A discrete event simulation model designed to achieve the objectives of disaster medical management (i.e. minimizing mortality and morbidity) in case of an MCI, has been presented. This simulation model provides the possibility to simulate a wide array of scenarios, health care levels and variable conditions. This allows for identification of emergent behavior and its impact on the prehospital MCI medical management. From this prototype tool it is possible to create a generic simulation model that encompasses enough parameters to provide evidence based recommendations for the management of medical disasters. For this particular scenario, we conclude that the best outcome for victims can be achieved by the combination of pre-triage, field-triage and quick distribution of victims to regional hospitals.

This simulation model offers the opportunity to test the effect of various MCI medical management decisions without the practical challenges of full-scale exercise and inherent ethical problems.

Future research will include additional scenarios such as CBRNE, terror and military battlefield situations, as well as modeling of the self-referral of MCI victims, triage incorrectness, decontamination process, in-hospital response and secondary transfer of victims. Finally, using historical MCI data is needed for optimal model validation.

Table 2: Overview of all statistically and clinically significant differences and best performing parameter settings for the TTT and TTH. Times are expressed in minutes.

Time	Parameter	Max. Mean Difference	Shortest Time
T1 TTT mean	Policy	3	S&R
	Field triage	3	Yes
T1 TTT maximum	Policy	12	S&R
	Transport supervision	8	Flexible
T2 TTT mean	Policy	37	S&PR
	Preliminary triage	11	No
	Field triage	20	No
	Transport supervision	51	Medium
T2 TTT maximum	Policy	85	S&PR
	Preliminary triage	11	No
	Transport supervision	93	Normal
	Distribution over hospitals	12	Closest First
T1 TTH mean	Policy	85	S&R
	Transport supervision	100	Flexible
	Distribution over hospitals	10	Closest First
T1 TTH maximum	Policy	100	S&R
	Field triage	10	Yes
	Transport supervision	143	Flexible
	Distribution over hospitals	20	Closest First
T2 TTH mean	Policy	53	S&R
	Preliminary triage	14	No
	Field triage	31	No
	Transport supervision	252	Normal
	Distribution over hospitals	28	Closest First
T2 TTH maximum	Policy	59	S&R
	Preliminary triage	16	No
	Field triage	31	No
	Transport supervision	429	Medium
	Distribution over hospitals	56	Closest First

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