A Concise Review of AI-Based Solutions for Mass Casualty Management

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Abstract. Disasters often result in mass casualty incidents, which trigger a series of complex decisions made at casualty collection points and advanced medical posts. The essential components in a disaster management chain are triage and casualty evacuation. Casualty evacuation without effective coordination may lead to overcrowding at hospitals and result in an increasing number of casualties. Thus, guidance for rapid transportation is needed according to triage categories, needed/available ambulances, human resources, and destination hospital capabilities. At casualty collection points, the process of medical decision-making is very complex as a significant amount of blood can be lost to internal bleeding, for example in the peritoneal, pleural, or pericardial areas, without any noticeable signs. This paper reviews several studies focusing on triage and evacuation guidance for a mass casualty incident (MCI) based on artificial intelligence.

Keywords: Mass causality incidents, triage, casualty collection points, advanced medical posts, mass causality management, AI-based solutions.

1 Introduction

MCIs are events in which the number of casualties exceed the available resources in the local area. They are often caused by transportation accidents, terrorism, fire, or natural disasters, called hazards [1]. A hazard is an event (natural or human-made) that can cause harm or loss [1]. They raise terrible destruction to physical structures, fatalities, and a massive demand of intervention to be handled when interacting with the community.

Mass casualty management (MCM) describes the process of attending to the victims of a MCI in order to minimize morbidity and mortality [2]. There are pre-established procedures for mobilizing resources, managing field, and hospital reception [3]. A multi-sectional approach is employed for the MCM model. This approach represents a form of a strongly linked rescue chain of responders for triage, field stabilization, and evacuation with healthcare facilities. The responders can be police, fire, search and rescue, an ambulance, or a pre-hospital team to name a few. Disasters in small isolated areas with limited resources, scarcity of materials, poor communication, and lack of preparedness often pose severe challenges to the management of victims [2]. MCM relies on expert knowledge of responders and incorporated links between the field and healthcare facilities through a command post [3].

A standardized system is required for managing communication and command and control (CCC) between response units in MCM. The incident command system (ICS) is a standardized structure responsible for a conjunctive response by multiple agencies. Disaster response can incorporate action from many different agencies. ICS ensures an effective response that the most pressing needs are satisfied, and the valuable resources are used efficiently.

Responsibilities of ICS include allocating an incident commander. ICS responsibilities are managed by the incident commander until delegated. They must oversee overall coordination of field operations, to include receiving reports from all other officers, continuously evaluating the general situation, coordinating requests between sectors in the field, and ensuring linkages between sectors.

When needed, the incident commander can delegate emergency management responsibilities. Thus, they will maintain the necessary focus on the overall picture of the disaster situation. The incident commander is often the local fire chief or commissioner.

Because of the multi-sectional structure of MCM, having a decision-making support system with real-time information is necessary for effective response in MCI events. AI-based decision support tools are aimed to assist in some areas of resource management in disaster response concerning a broad range of objectives and decision variables. These tools help people command faster and more efficiently.

In each phase of MCM, e.g., the search and rescue phase, several tools for decision-support can be used. Mishra et al. [4] proposed a state-of-the-art detection method based on computer vision and developed a large dataset for search and rescue in natural disasters utilizing drone surveillance. Perry et al. [5] introduced a triage method based on computer vision to provide real-time casualty information at the disaster scene for the MCI commander and the Emergency Medical Services (EMS) dispatch. More examples are given by Gaindric et al. [6].

The challenges presented by mass casualty events are much different from those faced by the daily healthcare system. In a MCI, the number of critically injured patients can be significantly larger and the injuries are typically quite varied. Effective decisions regarding the evacuation of mass casualty patients to the hospital must consider the distance from the MCI scene to the healthcare facility as well as its capacity. The healthcare facility capacity refers to the availability of beds when dealing with an overload of patients. Information regarding the real-time bed capacity of hospitals is one essential key to controlling the flow of patients from an MCI. In this case, it allows for evidence-based decision making regarding the evacuation of patients. Various decision support models have been proposed for resource management in disaster response. Several factors need to be considered to integrate into the triage process, such as available resources and disaster scale. This work focuses on three categories of AI-based decision support approaches: (1) traditional optimization-based decision support approaches; (2) reinforcement learning-based optimization techniques; (3) transport congestion detection methods.

2 Traditional optimization-based decision support approaches

Kamali et al. [7] developed a mathematical model based on resource-constraints to show how the scale of a disaster and availability of the resources affect the outcome of triage operations. The model analysis provided decision makers with optimal prioritization policies to maximize the expected number of survivors. Results are achieved with minimal data requirements; more specifically, the number of casualties in each category, the service times, and the number of servers available. Several main contributions to this work are: 1) Developing a tractable model that determines the optimal service considering the variation of casualties, service times, multiple servers, and multiple casualty types; 2) This model is compared with others in terms of both properties and performance; 3) Identifying structural properties of the optimal solution, extending and generalizing the work in other papers; and 4) Discussing important data issues, and more realistic problems.

Dean and Nair [8] proposed the Severity - Adjusted Victim Evacuation (SAVE) model. It focuses on the critical period immediately following the onset of a MCI and effectively evacuating victims to different hospitals, without overwhelming them. The "RPM" score evaluates the respiratory rate, pulse rate, and motor response. This model examines the hospital capacity and provides a guide to adjust evacuation decisions to increase survival rate. The causality severity levels affect the treatment time at hospitals, e.g., it takes more time to take care of severe cases with a lower score. Treatment capacities of hospitals are explicitly considered. The time and the location of the ambulance dispatch will determine their availability. The example scenarios assume three victim classes, each class consisting of fifteen victims. Finally, a single hospital is assumed for this example. The three victim classes are described as red, yellow, and green. Each model terminates when all patients are delivered to treatment facilities. It can be considered an effective model; however, using the SAVE model in practice may be challenging.

Mass Casualty Patient Allocation Model is presented in [9] can be used in two different ways: (1) to transfer real-time information concerning casualty counts, hospital driving time, and hospital bed capacity to enable more effective management of patient evacuation from one or more MCIs; (2) for training and planning as it allows for simulation exercises for evacuation from an MCI.

Amram et al. [10] proposed a new model called the spatial decision support system (SDSS). This system considers variables at an incident location such as hospital proximity and capacity and treatment specializations to help the incident commander in decision making. The SDSS system integrates road network and hospital information (e.g., beds availability) to estimate driving times in seconds to hospitals based on pre-computed times and displays the result in GUIs. The end-users can also point to the incident location on a map and make triage decisions with the assistance of the system. This model is constructed by two sets of data: road network data and hospital location data. The road network data from the Vancouver metro system with various variables such as traffic light and traffic sign locations for driving time calculations, and transportation control. These are essential because the travel time of an ambulance differs from that of a regular/commercial vehicle. The second set consists of Vancouver zone hospital information. This data set describes the capacity of a hospital and services it can provide. The GIS point features that represent these hospitals show the geocodes as close to the main accessible emergency facilities as possible.

SDSS [10] is potentially valuable for the prioritization in MCI evacuation decision making. The pre-calculated driving times from each casualty collection point to each hospital is the key component of the system. The performance of this model can be further improved if integrated with real-time traffic information and hospital capacity.

Treating and delivering casualties during a MCI needs to be made in a real-time and in sequential manner. Wilson et al. [11] described a novel combinational optimization model by employing a scheduling approach. The authors proposed a multi-objective optimization method that considers key factors in a MCI, such as the health level of casualties, the MCI scene, and appropriate hospital for each victim. They proposed a framework based on the Flexible Job-Shop Problem (FJSP) that can be adapted to accommodate the unique characteristics of the combinatorial optimization problem.

Wilson et al. [11] describes the flexible job-shop scheduling problem as a given set of machines $M = \{M_k\}, 1 \leq k \leq m$ and a set of Jobs $J = \{J_i\}, 1 \leq i \leq n$. J_i contains a set of n_i operations $O_{i,j}, 1 \leq j \leq n_i$. Machine $M_k \in M_{i,j}$ has time $M_{i,j,k}$ to process $O_{i,j}$, where $M_{i,j}$ is a set of machines. Assuming that all machines are free at the starting time of zero, each machine can only complete one operation at a time. The standard FJSP is aimed to optimize the total execution time by allocating the operations and machines optimally. Casualty processing is considered a FJSP variant, but some adjustments need to be done before mapping this problem.

1. Jobs $\rightarrow$ Casualties, $c_i \in C, 1 \leq i \leq n_c$, where n_c is the total number of casualties.
2. Operations $\rightarrow$ Tasks, $t_{i,j} \in T, 1 \leq j \leq n_{i,j}$, $n_{i,j}$ is denoted as the number of tasks related to casualty c_i.
3. Machines $\rightarrow$ Responder units, $r_k \in R, 1 \leq k \leq n_r$, where n_r is the total number of responder units.

According to [11], this model also considers additional variables. First, a set of hospitals $H = \{h_l\}, 1 \leq l \leq n_h$ to which casualties may be transported is required. Second, the transportation network is described as an undirected graph G which contains hospital, disaster zone, and emergency response station locations. Additionally, there are some variables about casualties that need to be consider such as the stabilization treatment requirement c_i^s, the extrication requirement c_i^e, and the triage level c_i^t. In this paper, four triage levels are assigned to casualties: T1, immediate, require immediate life-saving procedure; T2, urgent, require surgical or medical intervention within 2–4 hours; T3, delayed, cases that can be delayed beyond 4 hours; and T4, dead. A solution can be defined by a mapping $S: T \rightarrow R \times N \times H \cup \{0\}$, so that every task $t_{i,j} \in T$ has an associated responder $t_{i,j}^r \in R$, priority level $t_{i,j}^p \in N$ and hospital $t_{i,j}^h \in H \cup \{0\}$, where $h = 0$ for all tasks other than transportation tasks. The tasks within this model are distributed across a geographical area. It is also needed to calculate the driving time of response units from collection locations to pick up locations. Dijkstra's algorithm can be used to optimize responder travel times.

The five objectives considered in this multi-objective optimization method are [11]:

Tab. 1. The tasks and responders considered in the model of Wilson et al. [11].

	Name	Description
Task	Transport	All casualties require transportation to a hospital.
	Pre-transport, treatment	Before transportation, the casualties need to be stabilized or treated.
	Rescue	Casualties need to be extricated from debris and moved to treatment points.
	Pre-rescue, treatment	Some cases require stabilization before rescuing to ensure their safety.
Responder	Ambulance	A medical unit with equipment for both casualty treatment and transportation.
	MERIT	A mobile team that can travel to any MCI event and treat the casualties in place.
	HART	A "Hazardous Area Response Team" includes paramedics with required equipment and training to take care of casualties in urgent situations.
	SAR	A "Search and Rescue" team that is responsible for rescuing trapped casualties from dangerous environments.

1. $f_1(s)$ – the expected number of fatalities;
2. $f_2(s)$ – time in which casualties are transported on the fastest route to hospitals;
3. $f_3(s)$ – appropriate degree in which the hospital is chosen;
4. $f_4(s)$ – the idle time of response units;
5. $f_5(s)$ – time when a casualty reaches a hospital.

Predicting the number of fatalities $f_1(s)$ resulting from a response operation helps to save lives. This work helps to prioritize victims in a disaster and increase the survival rate. $f_2(s)$ helps the commander examine where a casualty needs to be transported. $f_3(s)$ helps to determine which hospital is appropriate for a casualty. $f_4(s)$ and $f_5(s)$ helps to allocate the responders reasonably. Furthermore, two factors, the dynamic capacity of each hospital and the effect of overload, should be considered for evaluating causality-hospital assignments.

The first decision that must be made is optimally assigning victims to hospitals. The following definitions are used for this decision process [11]: *Priority* – casualty priority; *Time* – how soon the task can start; *Dependency* – the number of tasks affected by task completion; *Location* – the distance between the current location of responders and the new task location. The second decision is made using three variables [11]: hospital capacity, appropriate treatment equipment, and distance between the current location and hospital location. Hospitals are iterated through based on proximity and current capacity.

3 Reinforcement learning-based optimization techniques

Ji et al. [12] introduced an effective model, based on deep reinforcement learning, for redeploying ambulances to minimize transportation time and increase casualty survival rate. Whenever an ambulance is available, it must be redeployed to a proper ambulance station to pick up the next victim. The authors propose a deep neural network called the deep score network to deal with the dynamic factors of ambulance stations.

This score [12] can dynamically redeploy a free ambulance with the highest score. The deep score network is trained using a policy gradient algorithm in order to minimize the pickup time of victims. Data is collected from the EMS system in Tianjin, China, consisting of EMS request records, road networks, ambulance stations, and hospitals.

Based on the Twitter data collected during Hurricane Harvey in 2017, a novel algorithm is developed for a better response to the requests of victims during a disaster [13]. It is one of the first approaches to deal with a large-scale disaster rescue problem using multi-agent reinforcement learning with social network data. The authors [13] designed a heuristic multi-agent reinforcement learning scheduling approach to handle multiple volunteers to quickly and effectively rescue disaster victims. This model can respond to dynamic requests and maximize performance over space and time with limited resources in large-scale areas for various conditions.

MobiRescue [14], or the human Mobility based Rescue team dispatching system, is based on a reinforcement learning application for disaster response. It maximizes the total number of responses for rescue requests and minimizes the driving time and the number of rescue units. This research scenario consists of a flooding disaster and uses the city-scale human mobility data set for Hurricane Florence. Because of the different impacts of flood disasters in different regions and the movement of people, the driving routes of the rescue team should be adaptively adjusted. They used a Support Vector Machine (SVM) [14] to predict the distribution of potential requests on each road segment. Based on this distribution, a reinforcement learning method is used. The data set used is recorded during 15 days in the Charlotte, North Carolina, and consists of the mobility of 8590 people.

A higher disaster impact often results in a higher demand for rescue. Moreover, the distribution of the movement of people during a disaster is a dynamic factor. The following he problem statement is proposed [14]: *"Given the available road network that vehicles can move after disaster in a form of satellite images (denoted as* $\tilde{G} = (\tilde{E}, \tilde{V})$*) and real-time distribution of people estimated using phone call requests. Requirements: how to predict the density of potential rescue requests and the rescue teams needed to serve as many victims as possible while minimizing the wasting time to the victims' position, and the number of rescue teams?"*

To solve this problem [14], they designed a system that consists of three stages (see Fig. 1): human mobility information derivation, predicting the distribution of potential rescue requests, and reinforcement learning-based rescue team dispatching.

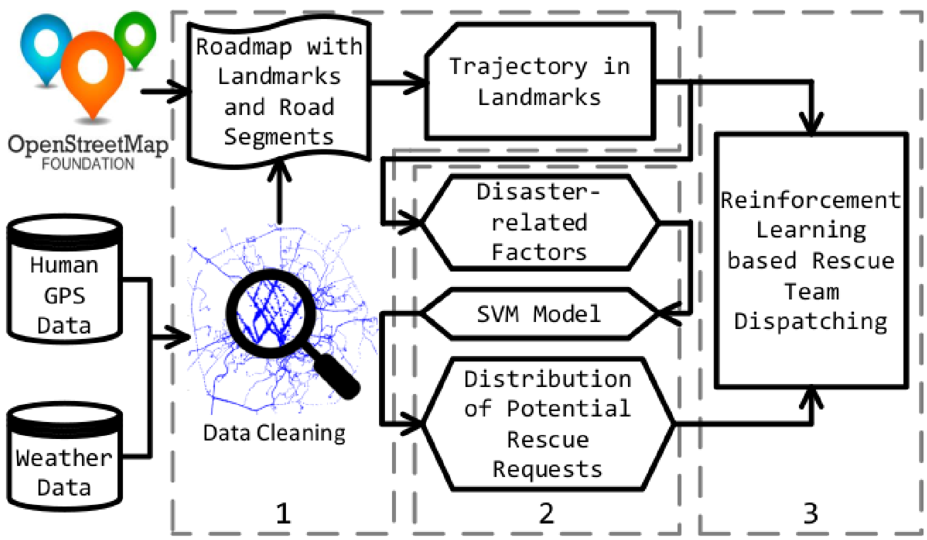

Fig. 1. The framework of MobiRescue [14].

A SVM model is employed [14] to estimate the distribution of potential rescue requests concerning many parameters. It focuses on hurricane-related factors represented as a vector *h = (precipitation, wind speed, altitude). Wind speed* and *precipitation* can be gained from the National Weather Service. *Altitude* can be extracted from the altimeter sensor on the cellphone of victims. The distribution of the movement of people also changes before, during, and after the disaster. The proposed reinforcement learning-based dispatching method determines the response of all rescue team requests in real-time. It runs on the predicted distribution of potential rescue requests.

The reinforcement learning model [14] is used to optimally guide the movement of the rescue teams that maximize the reward. The guided rescue teams respond to the rescue requests of the victims appearing on their driving routes. A Deep Neural Network (DNN) is used to obtain the optimal solution for dispatching rescue teams. In the training phase, historical distribution of rescue requests and the historical positions of rescue teams from previous disasters are used. Finally, the model outputs are used to produce a routing plan for each team during the disaster. Under calamity situations, the GPS locations of people may not be available. The authors used the historical GPS locations or home/work addresses to estimate the approximate locations. In conclusion, the authors conducted extensive trace-driven experiments to show the effectiveness of MobiRescue [14] to dispatch the rescue teams in real-time during a disaster. This practical approach can be applied to casualty transportation during MCIs with the output of this model as the routing guide for ambulances to available hospitals.

4 AI-based transportation congestion detection

During the casualty transportation process in MCIs, an important task needed to be considered is traffic state detection. In emergency situations, ambulances cannot transport casualties to hospitals in a timely fashion in order to receive further treatment if the ambulance falls victim to a traffic jam or blocked road way. This is especially prevalent in urban cities or when the disaster scenario causes severe destruction. Traffic state detection plays a vital role in the MCI response. The incident commander needs to determine which routes an ambulance need to drive to deliver casualties to hospitals with the least time delays. A popular and effective solution is using computer vision (CV) to detect traffic jams and blocked ways in MCI. In this section some specific solutions for this problem are reviewed.

In [15], the authors introduced a dynamic control system in Dhaka by measuring the traffic density from real-time video and image processing. The traffic density of a specific lane is estimated by detecting and counting the number of cars entering and leaving a lane with two cameras. The adaptive learning-based Mixture of Gaussian (MoG) method is employed to identify and count the number of cars in the lane. Once detecting and counting tasks have been done, the data is sent to traffic intersections hubs to estimate lane density.

Following this method [15], a dynamic traffic light control system at intersections hubs is built to regulate the traffic lights at intersections. Before deciding to change the traffic light, the system must check the neighboring hubs whether the lanes in front are free.

Unmanned Aerial Vehicles (UAVs) are used popularly and effectively in CV with high portability advantages. A combination of a UAV platform with AI is proposed to solve traffic congestion recognition problems [16]. Using UAVs, the traffic monitors can see the traffic scenes from all angles, receiving data faster and more cost effective. Their platform can be applied for casualty transportation to treat patients in a timely manner when a mass casualty occurs.

The framework in [16] consists of a monitoring system based on UAVs and a recognition system based on Convolutional Neural Networks (CNNs). In the former, a UAV embed route-planning technology captures the images of traffic scenes. These images are then transferred automatically to the recognition system by the UAVs. This module classifies whether these scenes are congestion or not. The result will be sent to the traffic-management center to determine further actions. The CNNs-based recognition system is installed on UAVs and can be divided into two blocks: feature extraction and feature recognition. The feature extraction block produces high-level features for given captured images. The feature recognition block receives these high-level features and results in a traffic state. The authors [16] used the pre-trained ResNet-34 model and a transfer learning method for the feature recognition block.

In casualty transportation, speed, density, and volume are the most crucial parameters for the commander to give a tactical decision in disaster response. Ke et al. [17] introduced a complete framework for estimating traffic flow parameters from UAV videos. This framework consists of four stages. The first two stages are for vehicle detection and the last two stages for traffic flow parameter estimation.

In [18], the authors constructed a UAVs benchmark for three tasks: Detection (DET) task, Single Object Tracking (SOT) task, and Multiple Object Tracking (MOT) task. The benchmark aimed to solve high density, small objects, camera motion, and real-time UAV platform issues. The authors focused on vehicles and the dataset of 100 video sequences selected from 10 hours of videos taken by UAVs in complex scenarios. The parameters like weather condition, flying altitude, camera view, vehicle category, vehicle occlusion, and out-of-view are considered. This UAV benchmark is a real-time solution in the CV. This benchmark can be used in patient transportation to select a dataset and an algorithm for applying CV based on a UAVs platform for traffic state detection during a MCI in useful ways.

Meng et al. [19] proposed a novel counting vehicle method based on expressway videos. This method mainly relies on four points: (1) constructing a new dataset named NOHWY that contains 7849 1920*1080 RGB images in diverse climatic conditions taken by Pan-Tilt-Zoom cameras from expressway; (2) a new vehicle correlation-matched algorithm for tracking to deal with trajectory point instability problem and solve interruption and uneven problems; (3) employing a motion vehicle trajectory optimization method; (4) counting multiple types of vehicles moving in different directions with a new multi-vehicle counting method.

The framework [19] can work effectively based on video sequences under different climatic conditions. This work can be used to build a decision support system in traffic state detection during casualty transportation in a MCI.

5 Conclusions

In a MCI, many victims often result in the overwhelming of emergency response resources for a particular area. In certain worst-case scenarios precious time is wasted when transporting seriously injured victims to a hospital.

Managing the emergency response in a MCI requires making many decisions. Depending on the scale of the incident and the severity of the injuries of the patients, these decisions may include how many resources are needed to respond to the incident or incidents, how to classify patients, which patients should get priority for transportation to a hospital, and to which facility each victim should be sent. Because of the time-sensitive nature of emergency medicine and the chaotic environment present at the scene of a MCI, these decisions must be made quickly and often with limited information.

Therefore, developing an effective framework is required. The models and solutions reviewed in this paper are some of the most effective frameworks dealing with this problem. However, these models still have some drawbacks when adapted to dynamic environments. With artificial intelligence development, building an AI framework for disaster response organizations can help incident commanders solve the crucial problems whenever disaster appear.

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