A Preliminary Optimisation-based Approach to Coordinate the Response of Ambulances in Mass Casualty Incidents

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ABSTRACT

Mass Casualty Incidents (MCIs) may occur with no notice and require a rapid response to manage the casualties and arrange their transportation to hospitals. MCIs may result in different numbers of casualties and fatalities. Further, response time can play a crucial role in reducing fatalities and protecting lives. This paper reports on a preliminary optimisation-based approach, termed MCIER, which has been developed to co-ordinate the response of ambulances to multiple MCIs. In this approach, a realistic representation of the road network is modelled for the geographical area of interest. Also, a Neighbourhood Search Algorithm (NSA) has been developed in order to find the optimum solution to the problem under consideration. A hypothetical case study of a MCI in Newcastle-upon-Tyne has been considered to investigate the effect on response time of the time of day, and day of week, on which the incident occurs.

Keywords

MCIs, Optimization-based approach, Co-ordination, Emergency response.

INTRODUCTION

Disasters, which can be classified as natural or man-made, can occur in a short time and cause widespread damage to infrastructure, humans, fauna and flora (Pereira *et al.*, 2011). Natural disasters may occur from severe natural phenomena such as floods, earthquakes and volcanoes (Lowes & Cosgrove, 2016). For example, the earthquake in Kashmir, northern Pakistan in 2005, killing 90,000 and injuring 110,000, and the Indonesia flood in 1815, killing 92,000 (Mackway-Jones & Wiley, 2012). However, man-made disasters may include deliberate terrorist activity (Mackway-Jones & Wiley, 2012) and can occur in places where a large number of people are present. Both natural and man-made disasters may result in significant loss of life (Centre of Trauma Sciences, 2016; Department of Health, 2007; NHS England National Emergency Preparedness Resilience and Response Unit, 2015; The UK Cabinet Office, 2017) which can be referred to as Mass Casualty Incidents (MCIs) (Lowes & Cosgrove, 2016). MCIs can result in different numbers and conditions of casualties, and numbers of fatalities, and thus the medical needs and the response plans required can be different (Frykberg, 2002).

The emergency response to a major incident involves the emergency services (ambulance, fire, and police) and hospitals, which need to work together and co-ordinate their activities to meet strategic goals (The UK Cabinet Office, 2017) such as protecting lives, minimising fatalities and reducing suffering. Therefore, the emergency response may require extra co-ordination and extraordinary resources (Lowes & Cosgrove, 2016; Mackway-Jones & Wiley, 2012). Further, MCIs pose challenges including high uncertainty, time pressure, a shortage of staff and, interdependencies and interconnections between multiple services and responders involved (Department of Health, 2007; Yi & Kumar, 2007; Lerner *et al.*, 2008; Mete & Zabinsky, 2010; Wex *et al.*, 2012).

Co-ordination issues that are relevant in MCIs are discussed in (Malone & Crowston, 1994; Chen *et al.*, 2008). Task allocation, or task flow, is one of these issues related to assigning tasks to the right responders to avoid overlapping and duplicating effort (Jotshi *et al.*, 2009; Amram *et al.*, 2012; McCormack & Coates, 2015). Variations of task scheduling are considered in (Gong & Batta, 2007; Jotshi *et al.*, 2009; Amram *et al.*, 2012;

Wilson *et al.*, 2013a; Repoussis *et al.*, 2016). For example, Wilson et al. (2013a) have considered task scheduling where each casualty is assigned to a specific hospital. Further, each responder is given a set of inter-dependent tasks related to the type of injury of a casualty. Repoussis et al. (2016) assumed that a limited number of tasks is assigned to each ambulance where the duration of each task is assumed to be known. Wilson et al. (2013a) and Repoussis et al. (2016) have modelled the stochastic travel time of the ambulances as a normally distributed random variable. They referred to the mathematical model suggested by (Kolesar *et al.*, 1975), and was extended in (Budge *et al*., 2010), where two equations are provided, each of which is used to calculate the travel time based on the type of the journey, i.e. long or short journey. However, the time and day of the occurrence of the incident are neglected which could have a negative impact on the response. Further, the prediction of the travel times of ambulances in urban environments, as modelled in the work presented in (Wex *et al.*, 2012), could be difficult to assume as such environments may be subjected to severe traffic.

Another co-ordination issue, as alluded to above, is casualty transportation. In MCIs, transportation involves transferring the right casualty to the right hospital at the right time using the right emergency vehicle. Modelling a realistic representation of a road network of the geographical area of interest, to be used by emergency vehicles during the MCI, is essential in order to design an accurate response plan. During a MCI, the road network might be affected negatively due to severe traffic, such as congestion, which may cause a delay in the response. A simplistic road network has been presented in (Amram *et al.*, 2012; Zhang *et al*, 2012; Muaafa *et al*., 2014; Repoussis *et al.*, 2016; Kamali *et al.*, 2017) where distances and the travel times between two locations in MCIs are assumed to be known upon model initialization. A realistic representation of the road network within the problem environment is represented in (Hawe *et al.*, 2015) with a sufficient level of detail, e.g. length and type of roads.

Considering the actual distance between two locations and constant speed are insufficient to predict the travel time where there are other factors, such as the type of road, the time of day, which could have an impact on driving in a normal and MCI situations. Dong et al. concluded that the type of road has a minor impact on the overall travel time. Further, the time of the day is conducted to have a minor effect in (Kolesar *et al.*, 1975; Budge *et al.*, 2010; Wilson *et al.*, 2013; Repoussis *et al*., 2016). In contrast, Schmid *et al.* (2010) reported that vehicles, including ambulances, would be affected by the increasing volume of traffic during the peak time which causes congestion. McCormack *et al*. (2015) established that the time and day has a significant impact on the speed of ambulance vehicles.

As mentioned, the focus of the research presented in this paper is on major incidents such as that of the bombings in multiple London sites in 2005 (London Assembly, 2006). Man-made disasters, such as terrorist attacks, occur with no-notice where the majority of such attacks predominantly take place in urban areas which can be densely populated. As such, a preliminary optimization-based approach (MCIER) has been developed incorporating a Neighbourhood Search Algorithm and a realistic representation of the road network in any geographical area of interest. Further, the traffic congestion is modelled by changing the speed of the ambulance vehicles based on the traffic at a particular time and on a specific day with the objectives of minimising the response and the idle time. The MCIER is designed to consider the factors of (a) time of day and (b) day of week on which the incident occurs. Also, the delays in the process of ambulance preparation, collecting casualties from incident sites and dropping-off casualties at hospitals are considered. The effectiveness of the time and day of occurrence of the incidents on the response time during MCIs is assessed by simulating the ambulance response to a hypothetical case study.

Contribution of this paper

In this paper, an approach has been developed, incorporating a NSA, to solve the problem of coordinating the response of ambulances in multiple MCIs. The co-ordination problem of the emergency response to multiple MCIs includes the allocation of ambulances to casualties and, subsequently, the allocation of casualties to hospitals. In the NSA, a number of structures have been developed to achieve the objectives of minimising (i) the overall response time to deliver all casualties to hospitals and (ii) the maximum idle time of all ambulances. In addition to the NSA, the approach includes a realistic representation of the road network in the problem environment under consideration, which provides a level of detail needed to generate ambulance travel times based on accurate distances of the routes to be used.

PROBLEM DEFINITION

The emergency response co-ordination problem consists of a number of casualties n_c, where $c_i \in C$ and $1 \leq i \leq n_c$ located at a number of incident sites n_{is}, where $is_i \in IS$ and $1 \leq i \leq n_{is}$. Further, each casualty needs to be transferred from an incident site to a hospital $h_i \in H$, where there are n_h hospitals and $1 \leq i \leq n_h$, by an ambulance $a_i \in A$, where there are n_a ambulances and $1 \leq i \leq n_a$. Also, ambulances are initially located at one of n_{as} ambulance stations $as_i \in AS$ where $1 \leq \mathrm{i} \leq n_{as}$. Each hospital has unlimited capacity and can accept any casualty, each of which has equal priority. In addition, all ambulances are considered to be the same and all are able to transport one casualty per trip to hospital. The speed of ambulances is modelled as depending on day of the week and time of day as indicated in (McCormack & Coates, 2015). Table 1 summarises the elements and parameters involved in the co-ordination problem. The solution to this problem has the objectives of minimising: (i) the overall response time, which represents the time to deliver the last casualty to hospital; (ii) the maximum idle time of all ambulances, which is the maximum time that an ambulance spends in an idle state. Thus, a solution method must make a number of allocation decisions including (a) which ambulance from which ambulance station to allocate to which incident site?, (b) which casualty will be allocated to which ambulance?, (c) which hospital should an ambulance carrying a casualty be allocated?

Elements	**Definition**
$\boldsymbol{C}$	Set of casualties
$\boldsymbol{IS}$	Set of incident sites
$\boldsymbol{H}$	Set of hospitals
$\boldsymbol{A}$	Set of ambulances
$\boldsymbol{AS}$	Set of ambulance stations
Parameters	
$\boldsymbol{n_c}$	Number of casualties
$\boldsymbol{n_{is}}$	Number of incident sites
$\boldsymbol{n_h}$	Number of hospitals
$\boldsymbol{n_a}$	Number of ambulances
$\boldsymbol{n_{as}}$	Number of ambulance stations
$\boldsymbol{S_d^{(t)}}$	Ambulance speed based on the day of week *d* and time of day *t*
$\boldsymbol{T_b}$	The time between receiving the initial emergency call to attend an incident site and an ambulance departing from the ambulance station
$\boldsymbol{T_d}$	On arrival at hospital, the time taken for an ambulance crew to drop-off a casualty before departing to collect another casualty
$\boldsymbol{T_c}$	On arrival at an incident site, the time taken for an ambulance crew to collect a casualty from the incident site and depart for hospital

Table 1. Problem elements and parameters

MODEL

The model of co-ordinating the emergency response to MCIs includes a problem environment being defined which includes a MCI scenario and a road network. Subsequently, a solution method is applied to the problem environment in order to create a response plan; please see Figure 1.

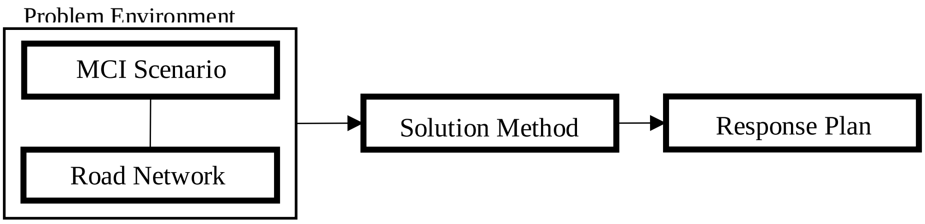

Figure 1. Overview of the MCIER approach

MCI scenario and road network

The problem environment requires a number of defined parameters to initialise the MCI scenario including the number and location of C, IS, H, A, and AS. A road network of the geographical area of interest is constructed using Ordnance Survey MasterMap (OSM) (Survey, 2019). It is one of the available sources of highly-detailed geographic data of Great Britain. The road network is represented as an undirected weighted graph $G = [V, E]$, where V is a set of vertices and E is a set of edges. Roads are represented by edges where each road has a type and a length. The start and end of each road are represented by vertices. The locations of ambulance stations and hospitals are established by converting their actual postcodes to the northing and easting coordinates using Grid reference (Gridfinder, 2011). Then, these are assigned to the nearest vertex in the road network. Further, incident sites are located at vertices.

Objective functions

In order to evaluate a solution, two objectives are used, $f_1(s)$ is the overall response time that represents the time taken to deliver the last casualty to hospital and $f_2(s)$ is the maximum idle time of all ambulances. The optimization problem is to find an allocation of tasks to ambulances, which first minimises $f_1(s)$ and second minimises $f_2(s)$, i.e.

$$f_1(s) = \max_{i,j} \sum_{k=1}^{n_t} TD_{k,i,j} \qquad\qquad f_2(s) = \max_{i,j}\ IT_{i,j}$$

where i and j indicate the i^{th} ambulance originally located at the j^{th} ambulance station respectively. Further, k represents the k^{th} task allocated to an ambulance, where n_t is the number of tasks. Also, the duration of each task, $TD_{k,i,j}$, assigned to an ambulance must be established. For example, the time taken to transport a casualty from an incident site to a hospital can be established using knowledge of the route to be taken in terms of distance and the speed of the ambulance based on day of week and time of day.

Solution method and response plan

Pseudo-code for the developed Neighbourhood Search Algorithm (NSA) is presented in Algorithm 1. The NSA produces a new response plan at each iteration. However, the previous plan will be kept unless an improvement is made in the new plan. At each iteration, an attempt is made to find an improved plan by selecting and applying one of five neighbourhood structures each of which makes changes to the current plan. The neighbourhood structures include (a) allocate a casualty to a different hospital (CH), (b) swap two casualties between two different ambulances (SCDA), (c) swap the position of two casualties in the same ambulance (SCSA), (d) move a casualty from one ambulance to another (MC), (e) assign a casualty from the ambulance that has the highest workload to the one that has the lowest workload (BW); please refer to Figure 2 for details. In relation to (e), this structure was inspired by the work presented in (Amiri *et al.*, 2010).

An initial solution is generated by allocating a number of tasks to each ambulance. These tasks are (a) travel to the incident site, (b) collect the assigned casualty, and (c) transfer the casualty to the assigned hospital. It is important to consider the possible delays that may occur during the response process which will affect the response time. Delays related to (a) the preparation time, (b) the collection time, and (c) the dropping-off time are considered. Figure 3 presents an example of how tasks are allocated to a single ambulance including the delays associated with each task. There is no prior knowledge, or assumption, of the duration of each task which depends on from where the casualty is collected and to which hospital the casualty is delivered. In relation to travelling to/from an incident site, and to/from a hospital, Dijkstra's algorithm is employed to find the shortest path between two locations. The effectiveness of the day and time on the response time for the same path has been investigated and is presented later in this paper.

Algorithm 1. NSA	
$\boldsymbol{plan} \leftarrow$ **INITIALIZE**()	Initialise response plan (*plan*)
Calculate $\boldsymbol{time}$ for $\boldsymbol{plan}$	
Define a set of neighbourhood structures $\boldsymbol{N_s}$	$N_s = \{N_0, \ldots\ldots, N_n\}\ where\ n = 4$
$\boldsymbol{i \leftarrow 0}$	Set the termination condition
While $\boldsymbol{i \leq n - 1}$ **do**	
$\boldsymbol{copyPlan} \leftarrow \boldsymbol{Plan}$	Preserve the original plan
$\boldsymbol{rand} \leftarrow$ **RND**()	$rand$ (0,4)
$\boldsymbol{op} \leftarrow$ **SELECT**($\boldsymbol{rand}$)	Select structure $op \in N_s$
Apply the selected structure $\boldsymbol{op}$ and generate $\boldsymbol{plan'}$	Create next $plan$
Calculate $\boldsymbol{time'}$ for $\boldsymbol{plan'}$	
if $\boldsymbol{time'} < \boldsymbol{time}$ **then**	
$\boldsymbol{plan} \leftarrow \boldsymbol{plan'}$	
Remove $\boldsymbol{copyPlan}$	
else	
$\boldsymbol{Plan} \leftarrow \boldsymbol{copyPlan}$	Retrieve the original plan
$\boldsymbol{i}$++	
end if	
end while	
Issue the final $\boldsymbol{plan}$	

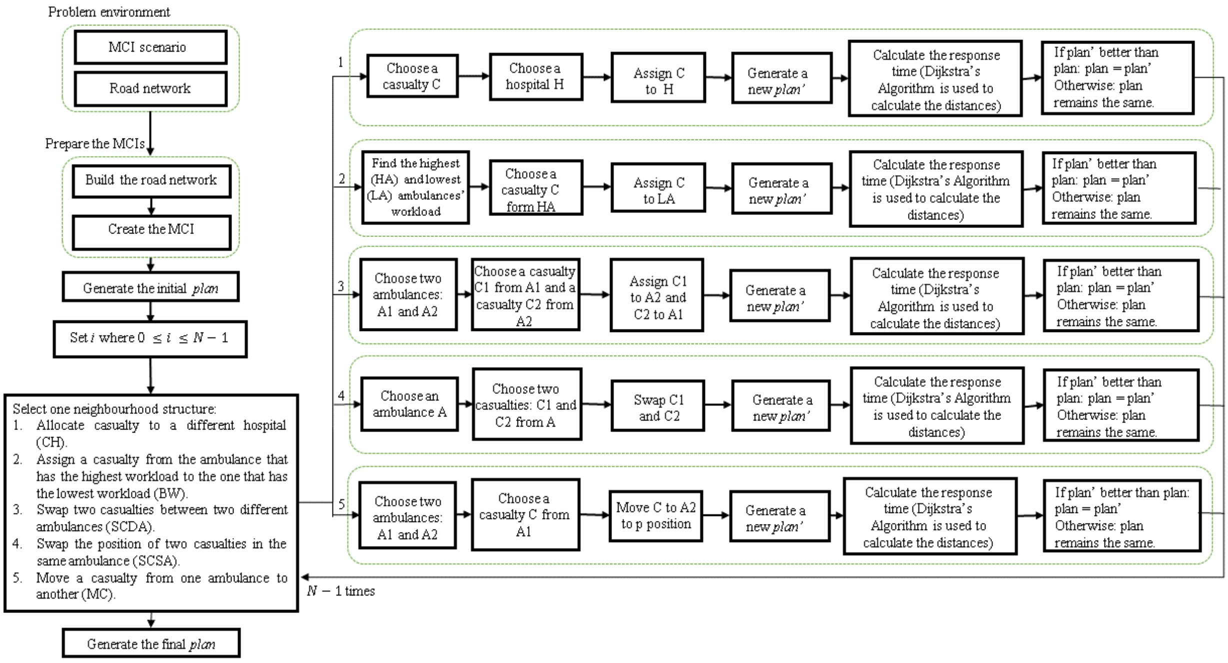

Figure 2. Details of The MCIER approach

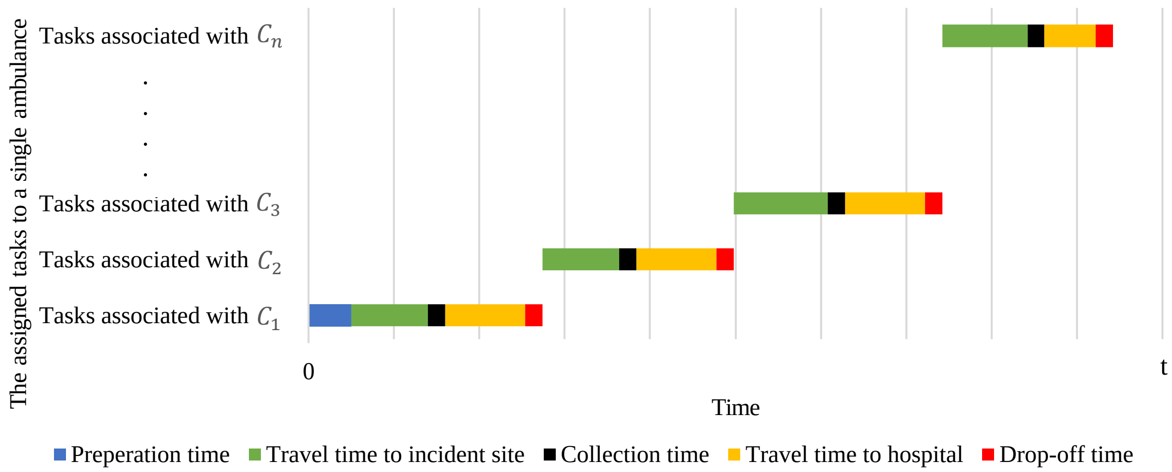

Figure 3. An example of the tasks allocated to a single ambulance

Validation

For validation purposes in terms of determining the best response plan, for a simple MCI problem, both an exact method, i.e. a Greedy Algorithm (GA), and the NSA were used. The simple MCI problem considered consisted of 12 ambulances initially distributed between 3 ambulance stations, 35 casualties distributed between 2 incident sites, with each casualty needing to be transported to one of 3 hospitals; please see Figure 4. The distances between locations are indicated in Table 2. The response time obtained by both the GA and NSA were the same, i.e. one hour and 32 minutes.

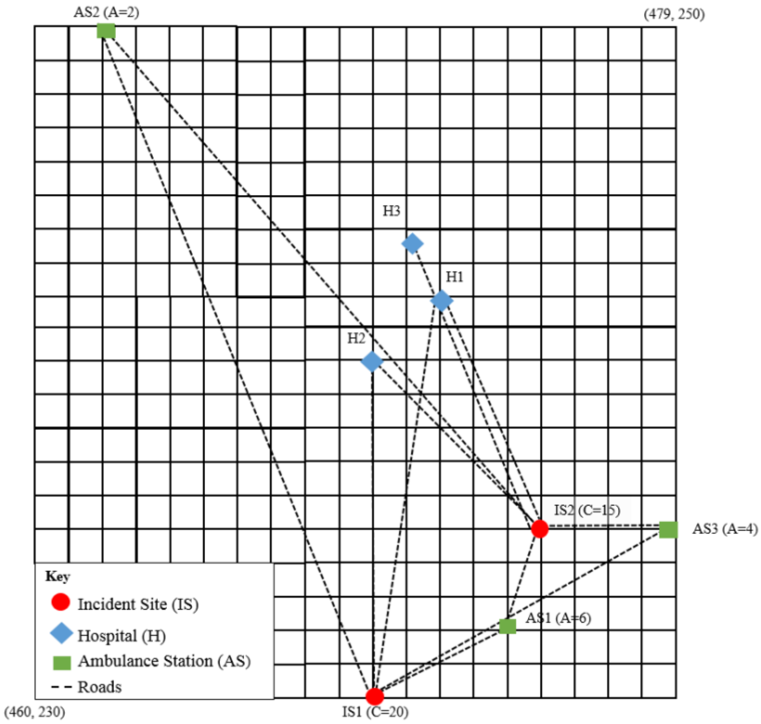

Figure 4. A Grid representation of a simple MCI problem

In this research, a NSA has been designed and used since the co-ordination problem will be further developed to include multiple dimensions such that an exact method will not be applicable (Hu et al., 2005). In addition, it is acknowledged that the execution of an exact method may be time-consuming whereas the NSA developed will not, which is critical in emergency response situations.

Another validation has been carried out for the road network using a route planner and Dijkstra's algorithm to ensure that the calculated distance between two locations is reasonable. A number of vertices have been selected on the map of the area of interest, which will be discussed later in this paper, and the distance between every two locations was calculated and compared. It is noticed that the path that was generated using Dijkstra's algorithm passes through buses and taxis lane which is not allowed in the AA route planner as it is created for normal vehicles. Further, ambulance vehicles are allowed to use some of the roads in an unintended direction if this would reduce the response time. However, this is not allowed for normal vehicles. Therefore, these reasons might cause minor differences in the total distance.

	IS1	IS2
AS1	4.47 km	3.16 km
AS2	21.54 km	19.95 km
AS3	10.30 km	4.0 km
H1	12.17 km	7.62 km
H2	10 km	7.1 km
H3	14.04 km	9.85 km

Table 1. The distance table for the simple MCI problem

CASE STUDY OF A HYPOTHETICAL MCI

Overview

Two incidents were assumed to occur on Sunday at 16:00 in the city of Newcastle-upon-Tyne in the North-East of England; Newcastle City Centre (NCC) and Byker Metro Station (BMS). These locations have been selected as such locations are densely populated and present major challenges for the emergency services in dealing with

MCIs (The UK Cabinet Office, 2017). Also, as indicated in Table 2, the environment consists of 2 hospitals including the Royal Victoria Infirmary (RVI) and Freeman Hospital (FH); 2 ambulance stations including St John Ambulance Station (SJA) and Sandyford Road Ambulance Station (SRA); 8 ambulance vehicles are located at SJA, and 7 ambulance vehicles are located at SRA. It is assumed that all ambulances are available when the incidents occur. The average speed of the ambulances during the time of the incident occurrences is assumed to be 23 km/h based on the average ambulance vehicle speed data presented in (McCormack & Coates, 2015). Figure 5 shows a representation of the road network of the city of Newcastle-upon-Tyne in which all locations of interest are labelled. The road network shown in Figure 5 consists of 7413 vertices and 9962 edges. The range of edge lengths is from 1.1 meters to 1145.4 meters. Only 9.1% of the edges are longer than 150 meters. The easting and northing of the top right coordinate of the map are (428014, 567866) and the bottom left coordinate are (422109, 563146) respectively. This case study aims to assess the co-ordination of the response to a multiple site MCI such that the response time is minimised, which is the time of delivering the last casualty from NCC and BMS to the RVI or FH. Also, the maximum idle time of all ambulances is minimised. The busy time, which is the duration of carrying out all the allocated tasks of each ambulance, and the idle time of each ambulance are recorded during the simulation.

Ambulance Stations		**No. Ambulance vehicles**	**(Easting, Northing)**
SJA	St John Ambulance Station	8	(422655, 564475)
SRA	Sandyford Road Ambulance Station	7	(425399, 565102)
Hospitals			
RVI	Royal Victoria Infirmary		(424457, 565003)
FH	Freeman Hospital		(426116, 567650)

Table 2. Hospitals and resources available at ambulance stations

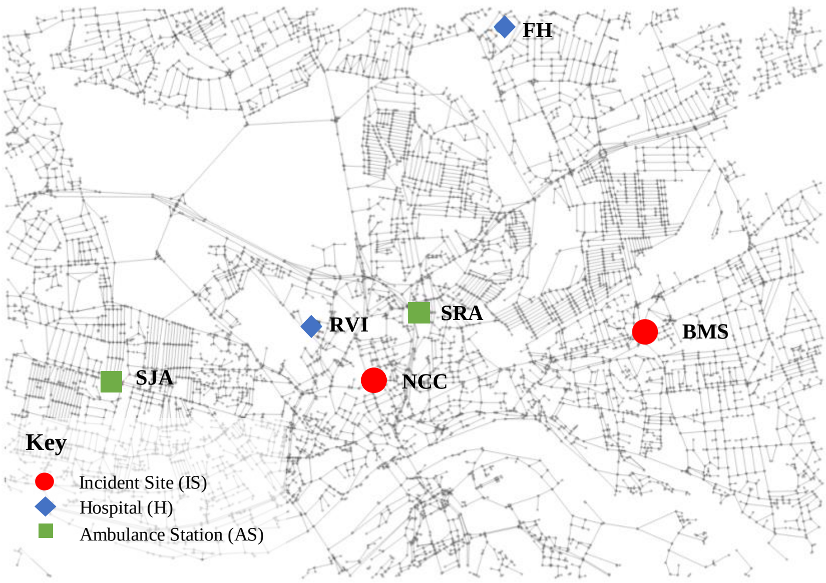

Figure 5. The road network map generated

Definition of scenario 1 and scenario 2

Both scenarios contain 35 casualties distributed between two incident sites (i.e. NCC and BMS) each of which has a different casualty distribution. In scenario 1, there are 25 casualties located at the NCC site and 10 casualties located at the BMS site. In contrast, scenario 2 involves 25 and 10 casualties located at the BMS site and the NCC site respectively. These two scenarios, with varying casualty distribution, were selected in order to find out to which hospitals the casualties will be delivered when the choice of hospital may not be intuitive.

PRELIMINARY RESULTS AND DISCUSSION

The algorithm was applied a hundred times, each time with 5000 iterations. The case study with two scenarios have been assumed each of which has a different casualty distribution; see Table 3 and Table 4. For both scenarios, the best four unique plans were selected and discussed. The NSA structures were evaluated in order to find their effectiveness on the response plan.

The response plans of the MCI scenario

Result for scenario 1

Table 3 presents the best four plans ($P1 - P4$) that all of which are unique and their corresponding response time. In all plans, the casualties located at the NCC site are all 25 transferred to the nearest hospital i.e. the RVI.

Plans	NCC (25)		BMS (10)		Response time (mins)	Total of casualties	
	RVI	FH	RVI	FH		RVI	FH
P1	25	0	5	5	47.5	30	5
P2	25	0	6	4	47.5	31	4
P3	25	0	7	3	47.5	32	3
P4	25	0	8	2	47.5	33	2

Table 3. A number of possible response plans ($\boldsymbol{P1 - P4}$)

Result for scenario 2

The best four plans ($P5 - P8$), along with their corresponding response time, were recorded. Table 4 presents these four plans all of which are unique. In all plans, most casualties located at both incidents are transferred to the closest hospital, i.e. the RVI, where only a few of the casualties at both incident sites are transferred to the FH.

	NCC (10)		BMS (25)		Response time (mins)	Total of casualties	
	RVI	FH	RVI	FH		RVI	FH
P5	10	0	22	3	70.6	32	3
P6	9	1	21	4	70.6	30	5
P7	9	1	18	7	70.6	27	8
P8	8	2	18	7	70.6	26	9

Table 4. A number of possible response plans ($\boldsymbol{P5 - P8}$)

In contrast to all four plans (P1 to P4) for scenario 1 in which all 25 casualties located at the NCC incident site were transferred to the RVI hospital, plans 6 to 8 in scenario 2 indicate that most casualties should be transferred from the NCC incident site to the RVI and one or two to the FH. Specifically, plans 6 and 7 have 9 casualties assigned to the RVI and 1 to the FH, whereas plan P8 has 8 casualties assigned to the RVI and 2 to the FH. In scenario 2, the reason why all casualties are not taken to the nearest hospital (RVI) is that doing so does not reduce the overall response time, i.e. the time to deliver the last casualty to hospital. That is, the ambulances to which these casualties are assigned do not lie on the critical path in terms of the overall response time.

The evaluation of the NSA structures

The NSA structures were evaluated to find the effectiveness of all structures in combination on the response time of the four plans generated for scenario 1 ($P1 - P4$) referred to in Table 6. It is noticed that the BW structure has a major effect on the response time as it made a number of improvements in all plans. It is noted that the SCDA, SCSA and MC structures will not change the overall response if (i) all casualties are the same and (ii) the casualties selected to be swapped are located at the same incident site and are assigned to the same hospital. However, since the casualties selected to be swapped may be located at different incident sites or allocated to different hospitals, then the overall response time will be affected (i.e. increased or decreased). For example, consider applying SCDA for two particular ambulances. A swap may decrease the overall response time if the next casualty allocated to an ambulance is located at the nearest of the multiple incident sites to the hospital at which it has just delivered a casualty. Conversely, this swap may increase the overall response time if the next casualty allocated to the ambulance is located at the furthest of the multiple incident sites to the hospital at which it has just delivered a casualty. Indeed, the same argument applies to the casualty allocated to an ambulance immediately prior to a swap being applied.

Plans	CH	BW	SCDA	SCSA	MC	Total no. of improvements	No. of iterations to reach the best plan
P1	3	25	1	0	1	30	1519
P2	0	38	1	1	2	42	1472
P3	**3**	**28**	**3**	**0**	**2**	**36**	**1372**
P4	0	25	2	2	5	34	1589

Table 5. The effectiveness of the NSA structures on the response time of plans $(P1 - P4)$

Further, the number of iteration of reaching the best response time for these plans is considered in the last column in Table 5. It is noticed that the best response time has been reached faster in plan P3 which is in the iteration 1372. In order to find the optimum plan between the proposed plans $(P1 - P4)$ in terms of idleness, the maximum idle time is recorded for all plans. Table 6 shows that the best plan of the four is P4 where the response to the MCIs is completed with the lowest idle time. Figure 6 illustrates the response plan of P4 including the delays in between tasks.

Plans	Idle Time (mins)	%
P1	8.00	16.8
P2	8.00	16.8
P3	8.00	16.8
P4	**6.00**	**12.6**

Table 6. The maximum idle time of plans $(P1 - P4)$

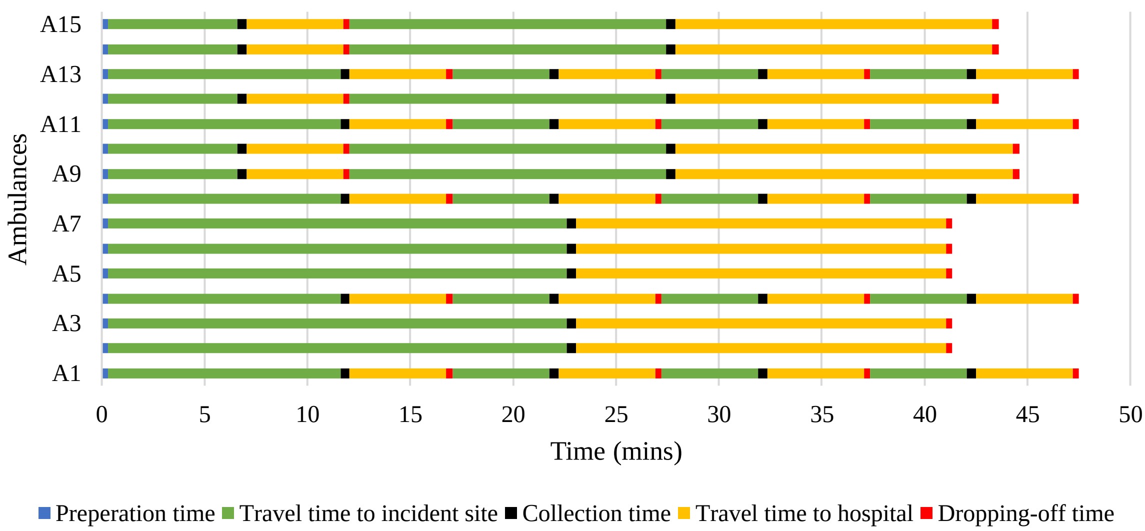

Figure 6. A Gantt chart of the response plan of scenario 1- $P4$

The effectiveness of the day and time on the response plan

The impact of the time of day and day of week on the response time has been investigated in scenario 1-$P4$. Different level of a traffic congestion have been considered based on the road traffic in a certain time of day. There are modelled by changing the speed of the ambulances where ambulance speed data is derived from the work presented in (McCormack & Coates, 2015). Figure 7 shows the differences in the response time when considering the same MCI scenario 1 but vary ambulance speed depending on different days and times. From

Monday to Friday between 5:00 and 16:00 the response times increase and fluctuate over the day based on the traffic congestion. However, on the weekend, the response times increase from 7:00 to 14:00 on Saturday and from 7:00 to 12:00 on Sunday. The response time reaches its minimum on most days at 5:00. The variation in the response time during the time of day and the day of week leads to the necessity of considering these variations when simulating the response to MCIs.

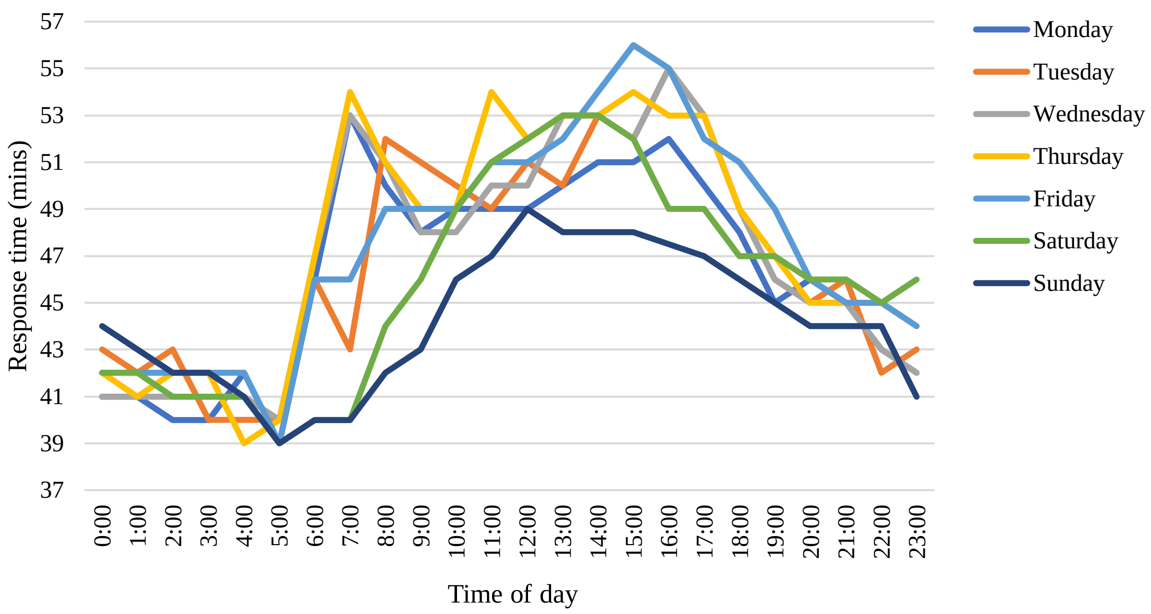

Figure 7. The response times of scenario 1- *P4* considering ambulance speed on different days and times

CONCLUSION AND FUTURE WORK

MCIs can result in different numbers and conditions of casualties, numbers of fatalities, and thus the medical needs and the response plans required can be different. The shortage of resources, i.e. ambulances, could affect the response operation. Thus, decisions should be taken in a coordinated manner. Co-ordination involves resource allocation (i.e. deciding which ambulance should be assigned to which incident), task allocation (i.e. which casualty is assigned to which ambulance and which hospital should a casualty be assigned to); all of these are crucial in order to distribute the resource among the casualties and avoid tasks overlapping.

In this paper, a NSA has been developed and used to produce the best possible plan for the proposed case study. The case study involved multi-incidents and was proposed to occur in Newcastle-upon-Tyne on a specific day and time, i.e. Sunday at 16:00. A number of experiments were carried out with varying casualty distributions between incidents. The objectives of the MCIER have been set to minimising the overall response time and, then, minimising the maximum idle time of all ambulances. An investigation has been made to find how the time of day and day of week affect the response time. The results show the necessity of considering the time and day of the incident occurrence when developing any MCI decision support system. There is more work to be done in the area of MCIs regarding modifying the current approach to be dynamic in nature. This will involve receiving and updating real-time information from the environment to improve the current response. Further, consideration must be given to the occurrence of new incidents during the operation as several MCIs could occur while the response to other incidents is ongoing. Finally, the capacity and treatment specialism of receiving hospitals, and the capacity of ambulances along with the dynamic nature of casualties' health state will be considered.

REFERENCES

Hu, J., Li, B., & Kihara, D. (2005) Limitations and potentials of current motif discovery algorithms *Nucleic Acids Research*, **33**, 4899–4913. doi:10.1093/nar/gki791

Amiri, M., Zandieh, M., Yazdani, M., & Bagheri, A. (2010) A variable neighbourhood search algorithm for the flexible job-shop scheduling problem *International Journal of Production Research*, **48**, 5671–5689. doi:10.1080/00207540903055743org/10.1080/00207540903055743

Amram, O., Schuurman, N., Hedley, N., & Hameed, S. M. (2012) A web-based model to support patient-to-hospital allocation in mass casualty incidents *Journal of Trauma and Acute Care Surgery*, **72**, 1323–1328.

doi:10.1097/TA.0b013e318246e879

Budge, S., Ingolfsson, A., & Zerom, D. (2010) Empirical Analysis of Ambulance Travel Times: The Case of Calgary Emergency Medical Services *Management Science*, **56**, 716–723. doi:10.1287/mnsc.1090.1142

Centre of Trauma Sciences (2016) *Pan London Major Trauma Networks: Response to Mass Casualty Incident*. London. Retrieved from http://www.c4ts.qmul.ac.uk/downloads/network-dox/lts-mass-casualty-response.pdf

Chen, R., Sharman, R., Rao, H. R., & Upadhyaya, S. J. (2008) Coordination in emergency response management *Communications of the ACM*, **51**, 66–73. doi:10.1145/1342327.1342340

Department of Health (2007) Mass Casualties Incidents – A Framework for Planning, 1–29. Retrieved from http://webarchive.nationalarchives.gov.uk/20130124035118/http:/www.dh.gov.uk/prod_consum_dh/groups/dh_digitalassets/@dh/@en/documents/digitalasset/dh_073397.pdf

Dijkstra, E. W. (1959) A note on two problems in connexion with graphs *Numerische Mathematik*, **1**, 269–271. doi:10.1007/BF01386390

Frykberg, E. R. (2002) Medical Management of Disasters and Mass Casualties From Terrorist Bombings: How Can We Cope? *The Journal of Trauma: Injury, Infection, and Critical Care*, **53**, 201–212. doi:10.1097/00005373-200208000-00001

Gong, Q. & Batta, R. (2007) Allocation and reallocation of ambulances to casualty clusters in a disaster relief operation *IIE Transactions (Institute of Industrial Engineers)*, **39**, 27–39. doi:10.1080/07408170600743938

Gridfinder (2011) Grid Reference Finder. Retrieved 1 August 2018, from https://gridreferencefinder.com/

Hawe, G. I., Coates, G., Wilson, D. T., & Crouch, R. S. (2015) Agent-based simulation of emergency response to plan the allocation of resources for a hypothetical two-site major incident *Engineering Applications of Artificial Intelligence*, **46**, 336–345. doi:10.1016/j.engappai.2015.06.023

Jotshi, A., Gong, Q., & Batta, R. (2009) Dispatching and routing of emergency vehicles in disaster mitigation using data fusion *Socio-Economic Planning Sciences*, **43**, 1–24. doi:10.1016/J.SEPS.2008.02.005

Kamali, B., Bish, D., & Glick, R. (2017) Optimal service order for mass-casualty incident response *European Journal of Operational Research*, **261**, 355–367. doi:10.1016/j.ejor.2017.01.047

Kolesar, P., Walker, W., & Hausner, J. (1975) Determining the Relation between Fire Engine Travel Times and Travel Distances in New York City *Operations Research*, **23**, 614–627. doi:10.1287/opre.23.4.614

Lerner, E. B., Schwartz, R. B., Coule, P. L., … O'Connor, R. E. (2008) Mass Casualty Triage: An Evaluation of the Data and Development of a Proposed National Guideline *Disaster Medicine and Public Health Preparedness*, **2**, S25–S34. doi:10.1097/DMP.0b013e318182194e

London Assembly (2006) Report of the 7 July Review Committee *Greater London Authority*, 157. Retrieved from http://news.bbc.co.uk/1/shared/bsp/hi/pdfs/05_06_06_london_bombing.pdf

Lowes, A. & Cosgrove, J. (2016) Prehospital organization and management of a mass casualty incident *BJA Education*, **16**, 323–328. doi:10.1093/bjaed/mkw005

Mackway-Jones, K. & Wiley, J. (2012) *Major Incident Medical Management and Support: The Practical Approach at the Scene* Third Edit. Wiley-Blackwell. Retrieved from http://healthindisasters.com/images/Books/Major-Incident-Medical-Management-and-Support-Third-Edition.pdf

Malone, T. W. & Crowston, K. (1994) The Interdisciplinary Study of Coordination *ACM Computing Surveys*, **26**. Retrieved from http://docenti.unicam.it/tmp/3687.pdf

McCormack, R. & Coates, G. (2015) A simulation model to enable the optimization of ambulance fleet allocation and base station location for increased patient survival *European Journal of Operational Research*, **247**, 294–309. doi:10.1016/j.ejor.2015.05.040

Mete, H. O. & Zabinsky, Z. B. (2010) Stochastic optimization of medical supply location and distribution in disaster management *International Journal of Production Economics*, **126**, 76–84. doi:10.1016/J.IJPE.2009.10.004

Muaafa, M., Concho, A. L., & Ramirez-Marquez, J. (2014) Emergency Resource Allocation for Disaster Response: An Evolutionary Approach *SSRN Electronic Journal*, 1–10. doi:10.2139/ssrn.2848892

NHS England National Emergency Preparedness Resilience and Response Unit (2015) *NHS England Emergency Preparedness, Resilience and Response Framework*. Retrieved from https://www.england.nhs.uk/wp-content/uploads/2015/11/eprr-framework.pdf

Pereira, A. H., Nardin, L. G., Brandão, A. A. F., & Sichman, J. S. (2011) LTI Agent Rescue Team: A BDI-based Approach for Robocup Rescue *Proceedings of the RoboCup 2011*. Retrieved from https://www.researchgate.net/profile/Luis_Nardin2/publication/235346574_LTI_Agent_Rescue_Team_A_BDI-based_Approach_for_Robocup_Rescue/links/02bfe511237be81faf000000/LTI-Agent-Rescue-Team-A-BDI-based-Approach-for-Robocup-Rescue.pdf

Repoussis, P. P., Paraskevopoulos, D. C., Vazacopoulos, A., & Hupert, N. (2016) Optimizing emergency preparedness and resource utilization in mass-casualty incidents *European Journal of Operational Research*, **255**, 531–544. doi:10.1016/J.EJOR.2016.05.047

Schmid, V. & Doerner, K. F. (2010) Ambulance location and relocation problems with time-dependent travel times *European Journal of Operational Research*, **207**, 1293–1303. doi:10.1016/J.EJOR.2010.06.033

Survey, O. (n.d.) *OS MasterMap Integrated Transport Network Layer user guide and technical specification - 30UG*. Retrieved from https://digimap.edina.ac.uk/webhelp/os/data_files/os_manuals/osmm_itn_userguide_v1.0.pdf

The UK Cabinet Office (2017) *National Risk Register of Civil Emergencies National Risk Register of Civil Emergencies*. Retrieved from https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/644968/UK_National_Risk_Register_2017.pdf

Wex, F., Schryen, G., & Neumann, D. (2012) *A Fuzzy Optimization Model for Scheduling and Allocating Operational Emergency Response under Informational Uncertainty: A Fuzzy Optimization Model for Scheduling and Allocating Rescue Units Canada*. Retrieved from https://epub.uni-regensburg.de/23331/1/ISCRAM_2012_-_Proceedings_version.pdf

Wilson, D. T., Hawe, G. I., Coates, G., & Crouch, R. S. (2013) A multi-objective combinatorial model of casualty processing in major incident response *European Journal of Operational Research*. doi:10.1016/j.ejor.2013.04.040

Yi, W. & Kumar, A. (2007) Ant colony optimization for disaster relief operations *Transportation Research Part E: Logistics and Transportation Review*, **43**, 660–672. doi:10.1016/j.tre.2006.05.004

Zhang, J.-H., Li, J., & Liu, Z.-P. (2012) Multiple-resource and multiple-depot emergency response problem considering secondary disasters *Expert Systems with Applications*, **39**, 11066–11071. doi:10.1016/J.ESWA.2012.03.016