International Journal of Information Systems for Crisis Response and Management

April-June 2013, Vol. 5, No. 2

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Research Articles

The *International Journal of Information Systems for Crisis Response and Management* is indexed or listed in the following: Bacon's Media Directory; Cabell's Directories; DBLP; GetCited; Google Scholar; INSPEC; JournalTOCs; MediaFinder; Norwegian Social Science Data Services (NSD); The Index of Information Systems Journals; The Standard Periodical Directory; Ulrich's Periodicals Directory

Modeling Uncertain and Dynamic Casualty Health in Optimization-Based Decision Support for Mass Casualty Incident Response

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ABSTRACT

When designing a decision support program for use in coordinating the response to Mass Casualty Incidents, the modelling of the health of casualties presents a significant challenge. In this paper we propose one such health model, capable of acknowledging both the uncertain and dynamic nature of casualty health. Incorporating this into a larger optimisation model capable of use in real-time and in an online manner, computational experiments examining the effect of errors in health assessment, regular updates of health and delays in communication are reported. Results demonstrate the often significant impact of these factors.

INTRODUCTION

Mass Casualty Incidents (MCIs) can arise in a number of disaster scenarios including, for example, terrorist attacks. They are predominantly characterised by the presence of a large number, relative to the level of available resources, of injured people who must be processed (that is, triaged, rescued, treated and transported to hospital) in as efficient a manner as possible. Deciding how such a processing operation should be carried out is a complex task, in that

DOI: 10.4018/jiscrm.2013040103

many inter-dependant decisions must be made in a coordinated manner and under challenging temporal constraints. One potential route to improved decision making is through the design and implementation of a decision support program.

When designing a decision support program for use in MCI response, we aim to produce a tool which will supply the decision makers with advice to assist in the formation of a high quality response operation. In an optimization based program, two components are of fundamental importance – the mathematical model and the optimization algorithm used to find solutions in the model. When considering our aim of delivering high quality advice, development on both components can contribute. The contribution of the optimization algorithm is particularly clear, where increasingly sophisticated algorithms can find higher quality solutions in a shorter time. However, the potential for focused model development to increase performance should not be overlooked. Poorly designed models which have neglected to include pertinent details or rely on invalid assumptions will, regardless of the optimization algorithm employed, lead to unrealistic and/or irrelevant advice being passed to the decision maker which, if followed, will result in poor performance. The potential benefit arising from the inclusion of a particular detail or feature into the model can be quantified through computational experiments, and therefore is directly comparable with any benefit afforded through increasingly sophisticated algorithms.

In the immediate response to an MCI two objectives of clear importance are the protection of human life and the minimisation of suffering (Cabinet Office, 2010). It follows that any model of MCI response should incorporate these objectives in some manner, possibly implicitly. In order to do so, careful consideration must be given to the nature of casualty health in MCIs, considering its representation, dynamic behaviour and the stochastic nature of its measurement.

Casualty Health in MCIs

In MCI response in the UK a triage system is employed when measuring the health of casualties. The purpose of triage (derived from the French *trier*, to sort) is to partition casualties into a number of categories which reflect the urgency with which they require treatment. The resulting information can then be used when deciding how to allocate scarce resources to a large number of casualties, prioritising those who are likely to benefit most.

Two triage systems are used in UK MCI response, each working at a different level of granularity. The first is triage *sieve*, which is carried out immediately following an MCI and must be completed before any treatment can take place. The outcome is the classification of each casualty into one of four categories as described in Table 1 (A. L. S. Group, 2011). A physical label, colour coded according to the triage category, is affixed to the casualty to allow for rapid recognition by other responders during the remainder of the response operation.

These categories are used in the first stage of the MCI response, where casualties must be extracted from the incident site and taken to a designated safe area, close to the incident site,

Table 1. The four health states used in triage operations.

Category	Description	Explanation
T1	Immediate	Require immediate life-saving procedure
T2	Urgent	Require surgical or medical intervention within 2-4 hours
T3	Delayed	Less serious cases where treatment can be safely delayed beyond 4 hours
T4	Deceased	-

where basic treatment can be administered in order to stabilise casualties and prepare them for transportation to an appropriate hospital. This area is known as the Casualty Clearing Station (CCS).

At the CCS a further, more detailed triage operation is carried out: triage *sort*. Essentially, triage sort allows for further detailed discrimination within the T1 class. A 0–12 integer scale is used, where 0 corresponds to Dead, 1-10 denote varying levels of severity within T1, and 11 and 12 denote T2 and T3 respectively. The triage sort score is used to prioritise casualties as they are transported from the CCS to a hospital.

The categorisation of casualties according to triage sieve and triage sort provides a natural representation of casualty health to be used in any mathematical model of MCI response. However, we note two aspects of this representation which pose challenges to its successful use. Firstly, despite the extensive training of Ambulance Service staff, the outcome of any triage operation is subject to error, both from measurement and from bias. For example, there is a documented tendency to assign children to triage states of higher severity than is actually warranted (Frykberg, 2002). When providing decision support based on triage information, the effect of such errors should be monitored closely. In addition, we note that the health of casualties is typically dynamic, and in particular is likely to deteriorate over time. This is reflected by current practice in triage sort, where casualties are re-assessed every 15 minutes in order to monitor any changes in their health. Predicting such dynamic behaviour is a significant challenge in its own right; again, the sensitivity of any proposed model to inaccuracies in such predictions should be assessed.

Casualty Health in Resource Allocation Models

Many decision support models have been proposed for use in disaster response problems where casualties are an important factor, with a wide range of approaches to the modelling of health exhibited. Where distinction between different health levels of casualties is made, not all models account for the movement between such health levels. Those that do typically fall into two categories: *simulating* health progression and analytically *predicting* it. In the case of the former, the models aim to realistically replicate the dynamics of any given casualty's health. In the case of the latter, the model aims to provide probabilistic estimates of how a casualty's health is likely to evolve over time, enabling the prediction of quantities such as the number of fatalities which will occur over a certain period:

No Health Level Distinction

Several decision support models designed for use in disaster response which do not explicitly model casualty health are described in the literature. Barbarosoglu and Arda (2004) describe a stochastic programming model designed to assist in deciding how first aid resources should be distributed across a disaster area. Whilst the health of casualties is not modelled explicitly, it could be argued that the demand for first aid resources at any one location within the disaster area includes implicit information regarding the health of the corresponding casualties. This is also the case for the resource distribution model proposed by Mete and Zabinsky (2010), which aims to satisfy the demand for resources at a number of hospitals. Casualties are included explicitly by Barbarosoglu et al. (2002), who propose a model to determine how helicopters should be employed to transport casualties from a number of locations to hospital. However, no distinction between the health of any two casualties is included.

A task scheduling model is proposed by Rolland et al. (2010), with an objective function which minimises a generic measure of cost. The model is extended by Wex et al. (2011), where the authors model the completion of relatively generic tasks and do not include any explicit modelling of casualties or their health. Wex et al. (2012) note that the tasks discussed may have time-windows for their completion and that as such a window could correspond to an expected survival time for a casualty, suggesting the authors envisage a possible application of their model where tasks are related to individual casualties. No explicit details of how such a casualty survival window could be determined are included.

Distinction but No Progression

Following models which do not account for any detail in casualty health, some examples of its inclusion at a basic level also exist. Chui and Zheng (2007) present a routing model describing the movement of evacuees out of a disaster area and the simultaneous movement of emergency responders into it. The model has the capacity to assign levels of priority to different groups of evacuees, which could be utilised to distinguish between groups with different average injury levels.

Casualties are modelled as 'clusters' by Gong and Batta (2007), to which ambulance responder units are to be assigned. Although the health of individual casualties is not modelled, the authors do allow for weights to be used to reflect the relative importance of each cluster of casualties. As in the work of Chui and Zheng (2007), these weights could be used to reflect average injury levels.

An example of including health information at the level of individual casualties can be found in the work of Yi and Ozdamar (2007), where a model describing the simultaneous routing of disaster relief supplies and transportation of casualties to hospital is described. Each casualty in the model is assigned to a weighted injury category, where the weights used are noted to be "subjective parameters". The model does not account for the possible evolution of health, nor the potential uncertainty in its measurement.

Progression Simulated but not Predicted

In some cases the dynamic nature of casualty health is captured through simulation. Jotshi et al. (2009) extend the work of Gong and Batta (2007) by incorporating a simulation of the response operations to run alongside a proposed decision support model. Casualties are modelled as belonging to one of two injury classes, with the deterioration of health possible in the simulation. No analysis of the effect of dynamic health levels is presented, nor is a model for analytically predicting how health will change presented. Similarly, Fiedrich (2006) discusses a decision support model designed to be used in conjunction with a simulation. Here, casualties may be in one of four health states and the evolution of health is affected by the casualty's environment. Health is assumed to be stable on arriving at a hospital.

Further examples of the simulation of casualty health can be found in the literature (Saoud et al., 2006; Rauner et al., 2012; Wang et al., 2012). Casualties in the agent based simulation of Saoud et al. (2006) may take one of five discrete health levels, the transition between which is modelled via a series of Markov chains. The parameters of the discrete time Markov chain (that is, its transition probabilities) are dependent on both the environment the casualty is in and the type of treatment (if any) they are receiving.

A discrete event simulation of the ambulance service response to MCIs is described by Rauner et al. (2012), where the health of casualties is described on a 0-100 scale. Health is assumed to fluctuate as casualties wait for, and receive, treatment. Such fluctuations are presumed to be of a linear form, with the survival time of each casualty sampled from a uniform distribution. The simulation model of Wang et al. (2012) incorporates two health state descriptions at different levels of granularity, similar to the triage sieve and sort systems described previously. The logistic function of Sacco et al. (2005) is employed to estimate the probability of survival of a given casualty, parameterised by their health state.

Progression Predicted

The work discussed above allows for the simulation of casualty health but not necessarily its prediction. This task is explicitly tackled by

Fiedrich et al. (2000), where a detailed model predicting the number of fatalities to arise from a given response operation is presented. Casualties are assumed to belong to one of two injury classes, information which is employed to predict the number of deaths arising from several causes including a delay in being rescued and a delay in receiving treatment at hospital. An exponential survival function is used in these calculations.

In contrast, a Weibull distribution of survival times is employed in the model described by Cotta (2011), which aims to assist in the allocation of casualties to operating rooms at a hospital following a MCI. The optimisation of treatment procedures is also the goal in the work of Tatomir (2006), although here the problem environment is the incident scene itself. Casualties in the model are assigned to one of four injury levels, and deterioration from one to another is assumed to occur at known points in time. For example, a casualty of health state P3 will move to health state P2 after exactly 120 minutes.

Uncertainty in Assessment

Only one work has been found which allows for uncertainty in the assessment of health. Jotshi et al. (2009) assume that several estimates of the health of a casualty, described as one of four possible health states, are available at the outset of the response operation. The authors propose combining these estimates via data fusion, following which the most probable health state is selected and used in the remainder of the model. However, no explicit analysis of the benefit of such an approach is presented.

Summary

A broad range of approaches to the modelling of casualty health have been reviewed. While some have omitted any explicit representation of health in their models, others have included the capability to distinguish between casualties according to their injury levels. The health of casualties may be assumed to be constant and deterministic. Alternatively, methods for simulating and for forecasting how health evolves, and in particular how casualties go on to die, have been proposed. However, no analysis of the effect of error in the assessment of casualty health has been found.

Where health is assumed to be of a dynamically evolving nature, any decision support program which involves predicting the outcome of a proposed response operation must predict how such evolution will occur. Developing such a predictive model is an extremely challenging task, with any errors potentially leading to poor performance of the decision support program. A natural question to ask is whether such poor performance could be mitigated through allowing the decision support program to be continually updated with the latest observations of casualty health, thus ensuring the impact of any past errors in prediction is minimised.

In this paper we propose to analyse the effect of uncertainty in health assessments in MCI response and the potential for regular information updates to improve performance. In order to do so we will first describe a scheduling-based decision support program for the MCI response problem, including a predictive model of casualty health. Moreover, details will be given on how it can be implemented in real-time in conjunction with a simulation of an MCI and its response. The results of computational experiments will then be reported and discussed, before conclusions are drawn and directions for future research are suggested.

MODEL

Scheduling Response Operations

The decision support model used in this research views the response operation of an MCI primarily as a scheduling problem, where tasks must be allocated to available responders and sequenced in such a way as to minimise an objective function. A further decision dimension is provided by the need to allocate each casualty to a hospital included in the environment. The modelled environment consists of a road transport network, represented as a graph, located on which are sites of interest, namely hospitals, fire stations and incident sites. Hospitals are given an initial capacity in terms of the number of casualties who may be admitted without the quality of care administered deteriorating. Within the environment, casualties are located at nodes on the transport network and are assigned an initial health state. Casualty health is represented by a dynamic probability vector for each individual $h_c = (p_1\, p_2\, p_3\, p_4)^{\mathrm{T}}$ where p_i denotes the probability that the casualty is currently in health state Ti (see Tab. 1) at that point in time. Each casualty is also described by a binary classification denoting whether or not they are trapped, in which case they will require rescuing by the Fire and Rescue Service through a "rescue" task.

The resources we consider are paramedic teams, each of which has an assigned ambulance, and fire-fighter teams, each of which has an assigned fire-appliance. Paramedic teams are initially located at one of the modelled hospitals, while fire-fighter teams are initially placed at fire-stations. The number of resources is set to be constant throughout the response operation. The tasks to be allocated to fire-fighters are rescue tasks, as mentioned previously. Paramedic teams may be assigned transportation tasks, detailing which casualty should be taken to which hospital. Paramedics may also be assigned stabilisation tasks, to be carried out at the CCS in order to stabilise the casualty and prepare them from transportation to hospital. Some paramedics may be trained as a Hazardous Area Response Team (HART) operative (Department of Health, 2008), allowing them to perform advanced stabilisation tasks within the dangerous areas of the incident site where casualties may be trapped and awaiting rescue from the Fire and Rescue Service.

A solution to this problem is a set of lists, each associated with a specific responder and detailing which tasks they are to carry out and in what order. In addition, for each transportation task the destination hospital must be identified. The resulting set of solutions forms a combinatorial optimization problem. Given a solution, a schedule of the response operation detailing the expected start and end times of each task can be constructed by considering any dependency relations which exist between tasks together with estimates of task duration and the time needed to travel between the locations of adjacent tasks.

Modelling Casualty Health

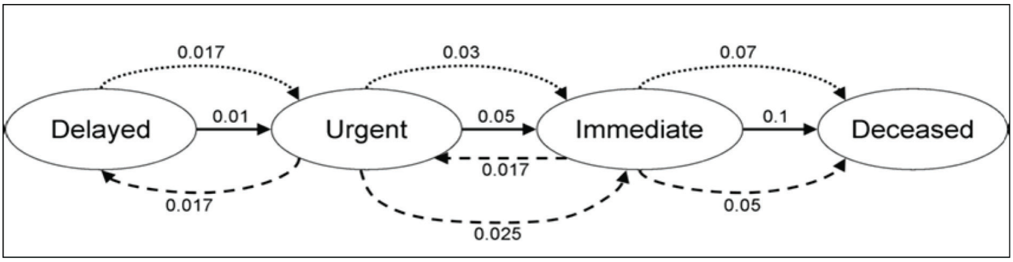
In order to compare any two solutions, an objective function is required. Having created a schedule for the solution in question, a set of discrete time Markov chains are used to predict changes in the probability health vector of each casualty in a manner similar to that proposed by Saoud et al. (2006). Three separate chains are used in order to distinguish between each of the three environments a casualty can find themselves in: trapped, waiting to be rescued; at a CCS, waiting to be transported to a hospital; and in an ambulance. The structure and transition probabilities of the three Markov chains are illustrated in Figure 1.

Given a health state vector $h_c\left(t\right)$ of casualty *c* at time *t*, if we know they will be in environment *k* for δ minutes then we use the Markov chain MC_k to predict the health state vector of casualty *c* at time $t+\delta$. Specifically, for each Markov Chain MC_k we denote the corresponding transition matrix as A_k, then:

$$h_c\left(t+\delta\right) = A_k^{\delta} h_c\left(t\right)$$

Given an initial health state vector $h_c(0)$ and denoting by t_c the scheduled hospital arrival time, we can estimate $h_c\left(t_c\right)$ for each casualty using the method described. We then define our objective function $f(s)$ as the expected number of fatalities after all casualties (the set of which we denote by *C*) have been transported to hospital:

Figure 1. Markov chain structure and transition probabilities, where the solid line corresponds to the "trapped" environment, the dotted line to the "at CCS" environment, and the dashed to the "in ambulance" environment



$$f\left(s\right) = \left(0001\right) \times \sum_{c \in C} h_c\left(t_c\right)$$

The scope of the proposed model extends to the point of casualties arriving at their designated hospital, after which point no further modelling of their health progression is carried out.

The parameters used in these probabilistic models should ideally be determined from an extensive analysis of data. However, in the area of MCI response such data is not freely available and as such the parameters used in this paper have been estimated. In order to better understand the behaviour resulting from this parameterisation it is useful to perform some descriptive analysis. Considering each environment, Figure 2 illustrates the probability of a casualty being Dead On Arrival at hospital, denoted P(D.O.A.), and its variation according to the time taken to deliver the casualty. For each environment, this analysis is conducted for casualties whose initial health state is T1, T2 and T3.

To further illustrate the behaviour predicted by the Markov chain model described, Figure 3 shows how the probability vector $h_c = (p_1\, p_2\, p_3\, p_4)^{\mathrm{T}}$ varies for a single casualty over a 30 minute period as they move through the three environments before reaching hospital, with T2 as their initial state.

Solution Methodology

In order to search the model's solution space a simple "best improvement" local search algorithm has been implemented, where at each iteration all neighbours of the current best known solution are evaluated and the solution with best improvement is selected. We note that such an optimisation algorithm may be prone to becoming trapped in local optima and subsequently failing to find globally optimal solutions, and leave it to further work to implement more sophisticated metahueristic algorithms with the potential to avoid such shortcomings.

Online Optimisation

Our model is designed for use in an online, real-time manner, where the computation timeline associated with the optimization algorithm is tied to the timeline of the response operation. Our model is continuously updated as and when new information is received while it searches the solution space. As opposed to starting the search process, waiting for some termination criteria to be met and then issuing the full resulting schedule, in the online model a responder unit queries the program as it nears the completion of its current task. At this point the program consults the best schedule found so far to determine which task should next be issued to the responder in question. This process is illustrated in Figure 4, where we see tasks being issued at time points t*, after which point they are fixed

Figure 2. The probability of a casualty being D.O.A., dependant on their initial health state, for (a) casualties trapped at the incident site, (b) casualties at the CCS, and (c) casualties in an ambulance

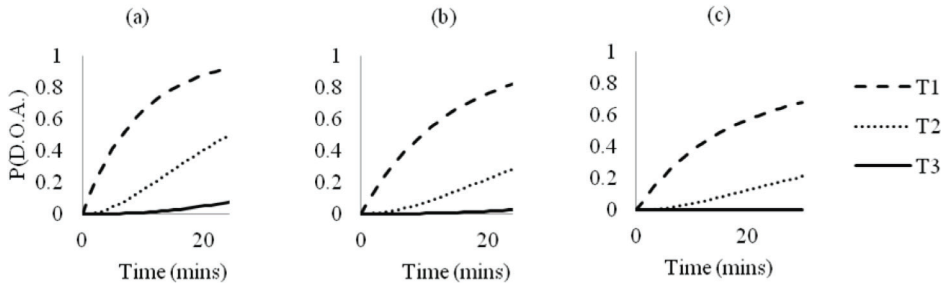
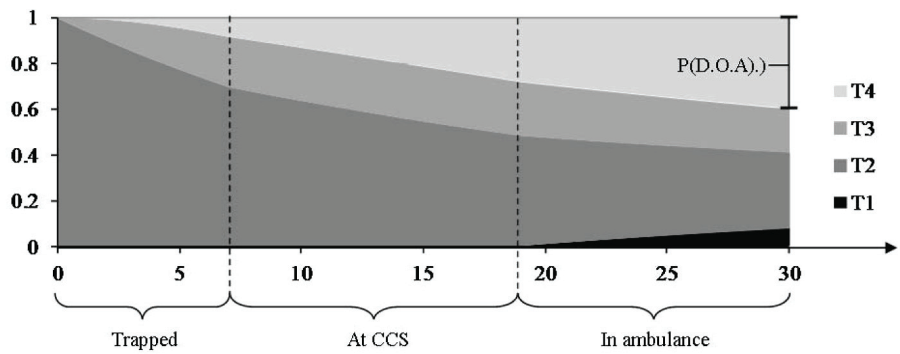


Figure 3. A simulated progression through each environment for a single casualty, displaying the changing probability of being in each health state at a given point in time



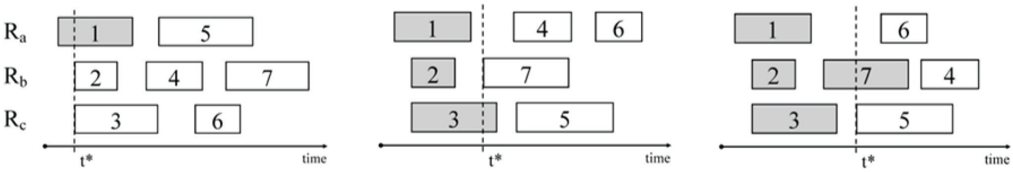
in the schedule while the remaining tasks can still be adjusted in the optimization process.

In order to test the online performance of the model, a source of real time information is required to replicate that which might be available during an actual response operation. For the purpose of this paper a simulation has been implemented to achieve this. The simulation works alongside the decision support program, receiving notification of tasks being issued to responders. At these points, initial estimates of the duration of the task are revised and improved to reflect the fact that the responder at the scene will be better equipped to make such estimates. Task duration estimates are updated once again upon the completion of each task. Finally, the health of each casualty is also simulated in a discrete sequence, using the same Markov chains used by the objective function and shown in Figure 1.

ANALYSIS AND EVALUATION

One hypothetical problem was used for all experiments, and was set-up using the *Scenario Designer* of the STORMI package described in (Hawe et al., 2012). The scenario involves five separate simultaneous terrorist attacks across London, each resulting in 18 casualties. The profile of casualty health at the outset of the response operation is defined by 22% in state T3, 50% in state T2 and 28% in state T1. The first thirty minutes of the response operation are considered, involving eleven paramedic teams together with five fire-fighter teams. Through computational experiments three quantities

Figure 4. An illustration of a rolling schedule being issued to three resources in real time



were examined to determine their effect on the utility of the decision support program: the accuracy of initial triage health assessments; the frequency with which re-triage is carried out; and the delay in passing new information regarding casualty health from the ground back to the decision support program.

Accuracy of Initial Health Assessment

The proposed decision support model assumes a full initial triage sort operation has been completed at time t=0. We note this is not an unrealistic assumption as the Ambulance Service explicitly state that all casualties must be triaged before treatment or transportation can begin (London Ambulance Service, 2007). The outcome of this triage operation is a classification of each casualty into one of the four health states described previously. In order to evaluate the effect of errors in these assessments we introduce an error parameter $e \in [0,1]$. Given a casualty with true health state T1, T2 or T3 an error in their assessment is simulated in a manner dependant on the true health state, with errors in assessment limited to health states adjacent to this. Denoting by A[Ti] the event that an assessment has led to the casualty as being labelled with health state i, the probability of these events for each true health state is shown in Table 2.

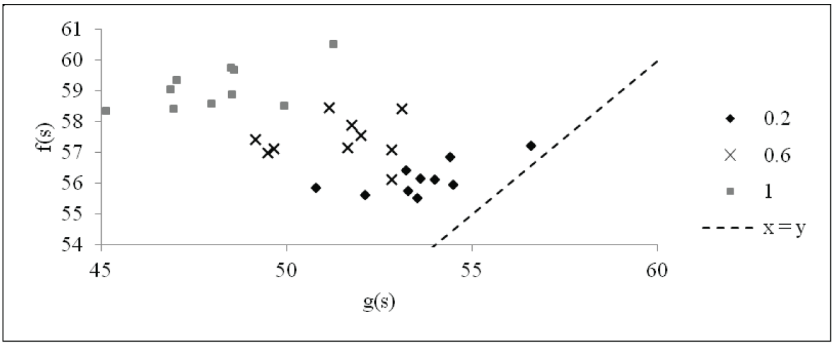
For errors of $e \in \{0, 0.2, 0.4, 0.6, 0.8, 1\}$ ten runs of five minute durations were performed, with two values recorded for each run. Firstly, we note the *perceived* objective value of the final solution, g(s). The *actual* objective value, f(s), is then calculated by replacing the health state of each casualty with the original value and re-calculating the objective value of the final solution. Some of these values are plotted together in Figure 5(a), where we see that an increase in the error of the triage assessment leads to a significant under-estimation of the number of fatalities resulting from the planned response operation.

The distributions of f(s) values for each of the six error levels are summarised in the box plot of Figure 5(b). When comparing the distributions associated with error levels of 0 and 0.2, no statistically significant difference was observed ($p = 0.083$) at the 5% significance

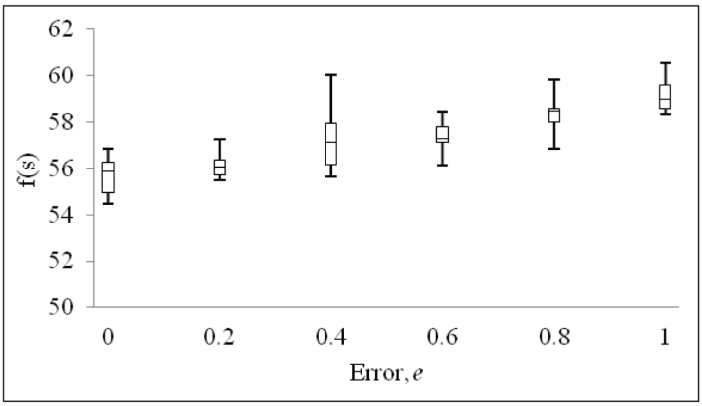
Table 2. The probability of health assessment outcomes with error level e

True Health State	P(A[T1])	P(A[T2])	P(A[T3])
T1	$1 - e/2$	$e/2$	0
T2	$e/3$	$1 - 2e/3$	$e/3$
T3	0	$e/2$	$1 - e/2$

Figure 5. (a) True vs. perceived objective values obtained after optimisation for three levels of error in the assessment of casualty health, (b) Distributions of true objective values obtained after optimisation for six levels of error in the assessment of casualty health



(a)



(b)

level when performing a t-test for equal means with assumed equal variance. The difference between error levels 0 and 0.4, however, was found to be statistically significant ($p = 0.0033$). This illustrates that the proposed model is relatively robust to errors in triage assessments.

Updating Health Information

In order to estimate the value of incorporating updates of dynamic casualty health, two extreme policies were compared. In the first, the health of each casualty is revealed only once, at the outset of the response operation. In the second case, updated information revealing the current health state of each casualty is received every minute, resulting in thirty updates per casualty over the course of the thirty minutes considered. In addition to these extreme cases, several intermediate policies were examined, corresponding to a varying number of evenly spaced updates of casualty health being received over the thirty minutes under consideration. Specifically, we considered policies of two, four and ten updates. In all cases, at the end of the thirty minutes the resulting schedule is evaluated using the actual health states progression of casualties as recorded by the simulation, so that comparisons may be made. Fifty runs for each level of update frequency under consideration were completed, with the resulting distributions of final objective values shown in Figure 6(a).

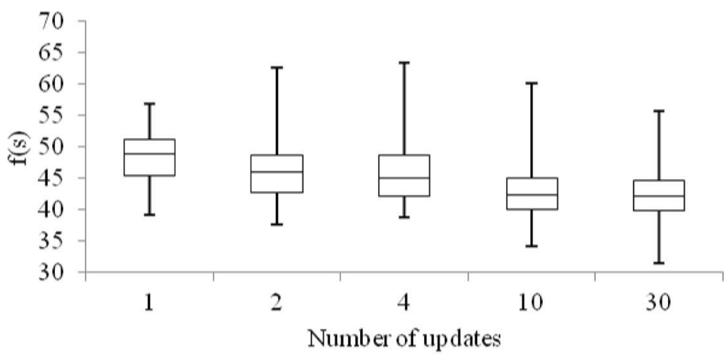
Further experiments were carried out to examine the effect a delay in the updates reaching the model may have on performance. For each instance, a policy of constant updating was employed, with a delay of one to five minutes imposed. Fifty runs were carried out for each level of delay. The results are shown in Figure 6(b).

We observe that updating every minute reduces the objective value from an average of 48.43 to 43.02 expected fatalities when compared with updating only once, thus providing an estimate of the value of casualty health information. Improvements are also observed across the intermediate policies. The relationship between objective value and the delay in information updates reaching the model is less well defined. While a five minute delay in receiving the information leads to 0.86 more expected fatalities on average, the difference was not statistically significant under a t-test for equal means with assumed equal variance (p = 0.161).

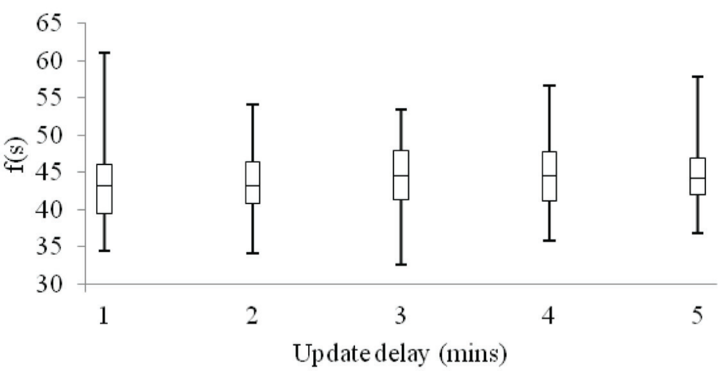
CONCLUSION AND FUTURE WORK

An online decision support program for use in response to Mass Casualty Incidents (MCIs) has been described. The model employed within the program allows for acknowledgment of the dynamic and uncertain nature of the health of casualties. Computational experiments were

Figure 6. (a) Final objective values against the number of updates over the thirty minute period, (b) Final objective value against the delay in updates reaching the model



(a)



(b)

carried out to examine the effect of errors in the assessment of health, with results demonstrating the model's relatively robust nature in this respect. Further analysis was carried out in order to quantify the benefit of re-assessing casualty health at regular intervals to ensure the decision support program is not working with out-of-date information. Finally, the effect of communication delays when passing information from the incident sites back to the decision support program was examined, with no statistically significant effect observed for delays up to five minutes.

This paper has shown that the dynamic and uncertain nature of casualty health should not be ignored when designing and implementing a decision support program for use in MCIs. We note that the health of casualties is only one of many sources of such uncertain and dynamic behaviour, with others including the time needed to complete tasks, the travel time between incident sites and the number of casualties located and requiring attention. As such, future research in this project will focus on further experimental analysis into the benefits of including these other pertinent details into the proposed model and analysing their impact. We also note that the online implementation described in this paper presents challenges in the design of optimization algorithms, due to the solution space constantly changing in both size and shape. Future work will focus on developing adaptive algorithms capable of adjusting to suit these changes.

ACKNOWLEDGMENT

This article is a revised and expanded version of a paper entitled "Estimating the Value of Casualty Health Information to Optimization-Based Decision Support in Response to Major Incidents" presented at Information Systems for Crisis Response and Management (ISCRAM) 2012, Vancouver, Canada. The authors gratefully acknowledge the funding provided by the UK's EPSRC (EP/G057516/1). The authors also thank practitioners from the Emergency Planning Units of Cleveland and Tyne & Wear, Co. Durham & Darlington Civil Contingencies Unit, Government office of the North East, Fire and Rescue services of Co. Durham & Darlington and Tyne & Wear, North Eat Ambulance Service, and Northumbria Police.

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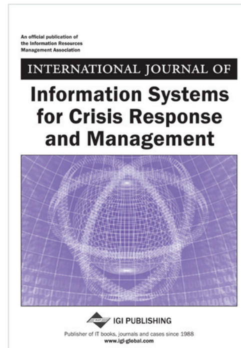

ISSN 1937-9390
eISSN 1937-9420
Published quarterly

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