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# Evaluation of centralised and autonomous routing strategies in major incident response

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ABSTRACT

Fast and efficient routing of emergency responders during the response to mass casualty incidents is a critical element of success. However, the predictability of the associated travel times can also have a significant effect on performance during the response operation. This is particularly the case when a decision support model is employed to assist in the allocation of resources and scheduling of operations, as such models typically rely on an ability to make accurate forecasts when evaluating candidate solutions. In this paper we explore how both routing efficiency and uncertainty in travel time prediction are affected by the routing strategy employed. A simulation study is presented, with results indicating that a routing strategy which allows responders to select routes autonomously, as opposed to being instructed via a central decision support program, leads to improvement in overall performance despite the associated increase in uncertainty in travel time prediction.



## 1. Introduction

A recent study (Zhou et al., 2011) has identified the "application of modern logistics technology" as a critical success factor in emergency management. One element of this application can be seen in the routing of emergency responders during a Mass Casualty Incident (MCI), which has a clear potential to impact on the quality of the overall response operation. This is particularly the case in the response operations of the Ambulance Service, which will involve making many journeys from the affected area(s) to appropriate hospitals. Effective routing decisions in making these journeys will lead to shorter travel times, which will in turn lead to a lower level of suffering and, potentially, a reduction in the number of fatalities.

The use of GPS technology to assist in making effective routing decisions is now commonplace, in the emergency services and more generally. However, the utility of a GPS system may be significantly affected in the period immediately following an MCI, when high levels of disruption (caused directly or indirectly by the incident) can lead to significant uncertainty in the time it will take to travel along a certain route (Jiang et al., 2012). The implication is that a purportedly optimal route specified by a GPS system, based on knowledge of the transport network under regular conditions, may in fact be sub-optimal in the disrupted disaster environment. In such cases it could be argued that routing decisions should be made with little regard to the guidance offered by the GPS system, with responders instead making decisions themselves based on their prior knowledge of the area and the knowledge acquired as they explore the now disrupted network. This is indeed what happened during the response to the Haiti earthquake, where it has been noted that drivers had "no maps with updated information and had to discover the best routes by driving and exploring" (de la Torre et al., 2012).

Considering the broader problem of resource allocation in MCI response, it has been noted (Altaya and Green, 2006; Simpson and Hancock, 2009) that mathematical models and optimisation algorithms could potentially provide decision support to emergency response personnel, leading to more efficient response operations. However, it is common for such models to rely on an ability to predict the outcome of any given response operation plan. Given this ability, the model can consider a larger decision problem than is feasible for emergency response personnel, accounting for decisions both immediate and in the near future, which in turn allows for better plans to be formulated.

Unknown levels of disruption in a transport network will present a significant challenge to any optimisation model of this type, as it will lead to difficulties in predicting travel times and, consequently, the outcome of the response plan. In this context, it may be beneficial to rely on a centralised specification of routes, acknowledging that the routes themselves may be sub-optimal, in order to improve prediction abilities. If the optimisation model were to release control over routing decisions to the emergency

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responders themselves, this would introduce uncertainty over route choice, thereby making the task of prediction more challenging. We hypothesise that this increase in uncertainty, and corresponding reduction in utility of the decision support program, could eclipse any benefit gained through better routing and subsequently shorter travel times.

In this paper we build on previous work which has introduced a scheduling-based decision support program for MCI response and demonstrated its sensitivity to uncertainty in temporal parameters (Wilson et al., 2012). Having previously ascertained that disruption to the transport network can be a significant source of such uncertainty (Wilson et al., 2013), in this paper we describe and evaluate routing policies designed to mitigate against these problems.

### 1.1. Routing in decision support systems for MCI response

Transport networks are not always explicitly modelled within decision support programs designed for disaster response. For example, Wex et al. (2012) present a scheduling model designed to assist in the allocation of response units to incidents, taking as input the travel times associated with each possible journey response units may make. Similarly, a travel time matrix describing the relation between points of interest is taken as problem input by Zhang et al. (2012) in the model of emergency responder allocation. This can be contrasted with work such as that of Yi and Kumar (2007) and Haghani and Oh (1996), where the transport network is represented as a graph, with each edge assigned a parameter describing the time needed to traverse it. Where such graphical representations of transport networks are included, it is common to assume their structure and parameters are deterministic and constant over time. This is true both of models designed to assist in commodity distribution over a large geographic area, such as those presented in Chang et al. (2007), Sheu (2007), Lin et al. (2011), and Tzeng et al. (2007), decision support programs using a scheduling formulation to assign tasks to emergency responders (Rolland et al., 2010; Wilson et al., 2012), and routing based formulation for the support of casualty transportation and evacuation (Chiu and Zheng, 2007; Yi and Ozdamar, 2007). By assuming all necessary information regarding the transport network is readily available, routing decisions can be made with confidence using a standard shortest path algorithm.

It is common in past work to use a reduced simplification of the actual transport network when representing it as a graph, an approach which can help avoid excessive computational burden. In the problem scenarios considered by Yi and Kumar (2007), for example, the most complex network considered contains 80 nodes connected by 1600 edges. Considering a geographic area large enough to encompass six cities in Turkey, the model presented by Ozdamar et al. (2004) represents the transport network using 12 nodes and 12 links, based upon motorway infrastructure. In contrast, a dense network comprised of 34,890 nodes and 43,445 links is used in the test problem considered by Jotshi et al. (2009), with a hierarchial decomposition employed to assist route computation in a timely manner.

Uncertainty in the disruption of the transport network has been incorporated to a limited extent using stochastic programming formulations. Examples include (Barbarosoglu and Arda, 2004; Mete and Zabinsky, 2010; Rawls and Turnquist, 2010), which consider a finite number of scenarios, each with assigned probability and associated network parametrization. Uncertainty is also acknowledged in the work of Jotshi et al. (2009), which extends the ambulance allocation model presented by Gong and Batta (2007) by including a data fusion step to estimate the level of damage and disruption on each road link. A solution methodology for finding optimal paths in a disrupted network following a disaster is presented in Zhang et al. (2013). The authors employ the network representation described by Yuan and Wang (2009), where the travel time associated with each edge of the transport network is assumed to increase over time in a manner which reflects its proximity to the disaster. A dynamic transport network structure is also modelled in the work of Fiedrich et al., 2000, with nodes and edges being added or taken away to reflect the impact of both the disaster and the response operation.

### 1.2. Contribution of this paper

In recent reviews of optimisation models for emergency logistics (Caunhye et al., 2012; de la Torre et al., 2012) it has been noted that there has been little research in the area employing stochastic models. Given the potential for an MCI to disrupt the transport network, directly or indirectly, and thus lead to uncertainty in routing and travel time prediction, this is clearly an area which merits further research. While some authors have acknowledged the possibility of disruption to the network and the subsequent uncertainty, it remains unclear whether or not this uncertainty will ultimately reduce the utility of a decision support program, and how any such effect depends on the choice of routing policy.

The remainder of this paper will be structured as follows. In Section 2 we will briefly describe a previously published scheduling based decision support program designed to optimise resource allocation in MCI response. In Section 3 we go on to present a simulation routine designed to generate random levels of disruption to the transport network representative of the problem environment. A number of potential routing policies will be introduced in Section 4, with details provided on the associated simulation of route choice and prediction of travel time. These policies will be compared using a Monte Carlo approach in Section 5, allowing for the uncertainty in the problem to be fully captured.

## 2. A scheduling model for disaster response

In this paper we employ the multi-objective optimisation model described in Wilson et al. (2013). The model is of a task scheduling nature, similar to the Flexible Job Shop scheduling Problem (FJSP) (Brandimarte, 1993). Specifically, each casualty in the problem is associated with a number of tasks which must be carried out by the available emergency responders. The tasks associated with each casualty will always include a *transportation* task, which requires an *ambulance* responder and involves the transportation of the casualty from the incident site $i$ to a chosen hospital $h$. Other tasks include *treatment* tasks and *rescue* tasks, and have a specific order in which they must be carried out in. This leads to a dependency structure in the scheduling model. A solution is defined by an ordered allocation of tasks to emergency responder units, together with a mapping from the set of casualties to the set of hospitals. Given such a solution, the first stage in its evaluation is the creation of a corresponding schedule by estimating the time at which each task will start and finish. This involves estimating the duration of each task, respecting the dependency relations which exist between them, and estimating associated travel times.

An example segment of a response schedule is given in Fig. 1, where the initial schedule of two responders $r_1$ and $r_2$ are shown. In addition to displaying the tasks to be carried out, movement between different areas in the MCI environment are shown.

As can be seen in Fig. 1, the accurate estimation of travel times is an essential part of computing an accurate schedule. The objective functions which measure the quality of a given schedule primarily use the estimated start and end times of tasks in their computations, implying that the accuracy of travel time estimation will directly affect the model's ability to accurately compare solutions and select one of high quality.