A WEB- BASED MODEL TO SUPPORT TRIAGE LOCATION ALLOCATION IN MASS CASUALTY SITUATIONS

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ABSTRACT

Many aspects of life in North America changed in the aftermath of the terrorist attacks that took place in the United States on September 11, 2001. In addition to the implementation of new security protocols and the strengthening of those already in existence, there were also more subtle changes. Within the medical community, for example, it became evident that existing strategies for managing mass casualty incidents (MCI) were insufficient when dealing with large-scale terrorist attacks (Frykberg 2002; Frykberg 2003). In a position statement made by the American College of Surgeons (2003), it was acknowledged that a smoother integration of rescue, decontamination, triage, stabilization, evacuation and definitive treatment of casualties was required in order to enable the system to provide the best care to the greatest number of casualties in a mass casualty situation (American College of Surgeons 2003; American College of Surgeons 2010). This thesis introduces a web based spatial decision support system (SDSS) intended to assist health care providers at the scene of an MCI in determining the appropriate hospital to which critically injured patients should be evacuated. The model decision-making process utilizes the following factors in determining the evacuation hospital: proximity of the hospital to the MCI, hospital capability and real time bed capacity. The analysis and visualization associated with the SDSS incorporates spatial network analysis as well as specialized algorithms for calculating travel times. This is the first known SDSS to target and attempt to optimize decision-making processes during critical stages of evacuation.

Keywords: Mass Casualty, GIS, SDSS, Spatial Modeling, Emergency Services

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INTRODUCTION

1.1 Overview

Though infrequent, mass casualty incidents put a heavy burden on the healthcare system, often requiring either outside assistance and/or a shift in resources in order to accommodate the large influx of severely injured patients by which they are characterized (Levi, Michaelson et al. 2002; Hammond 2005). Defined by the American College of Surgeons, as an incident of such large scale or severity that it cannot be handled by the healthcare system, mass casualty incidents often overload the system causing breakdowns at the initial triage stage (American College of Surgeons 2010). Providing care to critically injured patients during a mass casualty is much different than providing care to critically injured patients under normal circumstances. In a mass casualty, the emphasis shifts from caring for the individual to saving as many lives as possible. This requires a different set of skills and management protocols.

In the aftermath of the September 11th terrorist attacks, there has been a renewed focus on mass casualty research. To date, much of the research in this area has centred on hospitals' ability to treat patients and on improving methods for conducting primary triage at the pre-hospital stage. Although the determination of evacuation priorities during a mass casualty has received relatively little attention, the decision as to where critically injured patients should be evacuated is of great significance as it can directly affect both the rate at which patients receive care and the type of care the patients receive. This decision can also affect the level of care received by other critically injured patients, as in a mass casualty situation, resources need to be distributed in the most efficient fashion.

Within Canada, mass casualty research is quite limited. This is likely due to the limited number of mass casualties that have occurred within this country and to the fact that American research, which is far more robust in this area, is also relevant within the Canadian context, particularly as it relates to triage practices and emergency services.

This thesis presents the first web-based, mass casualty evacuation prioritization model that provides users with real-time information regarding the appropriate hospital to which patients should be evacuated. The model uses ambulance driving time calculations to determine the proximity of the MCI to each of the hospitals in the study area and includes real time updates concerning hospital capacity, capability and driving time. Because the model is web-based, it can share information between several different locations in real time (a model can be created for each location). As a result, it can be used in situations where several MCI's occur simultaneously. The model can be used by first responders at the scene of an MCI or for the purpose of advance planning. For example, the model could be used to examine proposed locations for large scale events, conferences, etc. in relation to health care facilities or to help to determine where to position a mobile health facility in relation to a particular event.

1.2 Research Problem

During a mass casualty, the number of critically injured patients is significant and the injuries are typically quite varied and severe in nature (Frykberg 2004). Mass casualties also require a shift from a patient-focused style of treatment to a more efficiency-based model in which the goal is to save as many people as possible (Kennedy, Aghababian et al. 1996). Pre-hospital trauma support guidelines state that critically injured patients should be transferred to a level 1 trauma hospital (Einav, Feigenberg et al. 2004). This works well for an exclusive trauma system, in which there are only one or two major health care centers providing critically injured patient care. Within an inclusive trauma system, however, where all acute care hospitals participate in providing care for critically injured patients, patients are typically sent to the nearest acute care hospital capable of caring for the patient(Physician 1993; Nathens, Maier et al. 2003; Utter, Maier et al. 2006). In Canada, most of the major metropolitan area trauma systems are inclusive (Hameed, Schuurman et al. 2010).

Deployment of emergency services personnel to the scene of the incident and preparation of nearby hospitals to receive patients is standard practice in the management of mass casualty incidents (Davis, Poste et al. 2005). Once on scene, the senior paramedic begins organizing the triage process and determining evacuation priorities. He or she also determines the hospital/s to which patients will be sent, basing his/her decisions on past experience, in addition to knowledge of hospital proximity, capacity, specialty and trauma level (Emergency Health Services 200). Hospital capacity is measured in terms of bed availability and is a crucial component in the provision of patient care. A hospital`s ability to care for critically injured patients is also correlated to the flow of patients arriving into the hospital (Frykberg 2002; Hirshberg, Scott et al. 2005).

Hospital proximity plays a major role in determining where patients will be sent. In fact, studies show that during a mass casualty, patients are typically evacuated to the nearest hospital (Einav, Feigenberg et al. 2004; Aylwin, König et al. 2006). Proximity is also important for EMS models that are non mass casualty related, like those that assist with optimization of ambulance and fire truck location in order to provide service within a certain area based on estimated time of arrival (Hogan and ReVelle 1986; Gendreau, Laporte et al. 1997). Such models also typically include driving time as a variable (Derekenaris, Garofalakis et al. 2001; Huang and Pan 2007). Using GIS, proximity can be measured using several different methods, the most common being Euclidian distance, Manhattan distance and travel time calculation over a road network. Euclidian distance, which simply calculates the straight line distance between two points on a road network is not compatible with an MCI evacuation model (ESRI 2006). Manhattan distance, which measures the distance between two points on the road network (ESRI 2006), provides more accurate results than Euclidian distance, but the exclusion of travel time and impedance values renders it unsuitable within an MCI evacuation context. Travel time over the road network, in that it looks at distance, speed limits and impedance values (traffic lights, stop signs, etc.), provides a much more suitable means of measuring proximity within an MCI evacuation framework (ESRI 2006).

To date, most MCI research has focused on the management of hospital surge capacity, however, it may also be possible to prevent or delay surges by better directing the flow of patients during the initial stages of evacuation. As far as the author is aware, a means of providing information concerning patient flow to those at the scene of a mass casualty incident has not yet been developed.

However, it would be interesting to examine the grey literature to determine whether a model has been developed for use by military or government.

1.3 Research Objective

The objective of this project is to create a model that will assist health care providers in determining evacuation priorities in the case of a mass casualty. Designed to allow first responders to more easily and accurately determine the appropriate hospital for the evacuation of patients from a mass casualty, the model provides information critical to the decision-making process within a matter of seconds. This includes driving times to the nearest hospitals, the trauma service level of each hospital, the location of hospitals in relation to the incident, and up to date hospital capacity.

There are two primary user groups for this model: the first group is made up of those health care professionals (first responders) responsible for evacuation decision making. The second group is made up of health care administrators who would use the model for risk management modeling and planning.

1.4 Background and Context

1.4.1 Key Elements of Mass Casualty

Mass casualty incidents are those that, by the sheer number and severity of casualties, overwhelm the health care capacity within a given community (Hammond 2005; Shoher, Chang et al. 2006; Lennquist 2007). This definition emphasizes the crucial role played by triage and trauma centers in maximizing capacity during a mass casualty incident (Frykberg 2004). One of the key elements in the successful management of mass casualty incidents is the rapid evacuation of patients to the appropriate health care facility (Sampalis, Denis et al. 1999; Aylwin, König et al. 2006). Within exclusive trauma systems, where one major center provides care for all critically injured patients, this is quite simple to organize (Lansink and Leenen 2007). However, in the case of inclusive trauma systems, where there exist multiple hospitals with varying trauma designations, decisions as to where critically injured patients should be sent are somewhat more complex (Nathens, Brunet et al. 2004; Utter, Maier et al. 2006). In these cases, the decision is typically based on the hospital's proximity to the MCI location, its capacity and trauma level, and the type of injury involved (Aylwin, König et al. 2006). In these systems, the process of sorting patients based on injury type and severity, also known as triage, has a profound impact on the evacuation effort (Nathens, Maier et al. 2003).

1.4.2 Mass Casualty Triage

A critical component in the effort to maximize the number of casualties who survive, MCI triage is probably the most researched subject in mass casualty. A concept that originated on the battlefield, triage refers to the process of prioritizing medical care based on the medical condition of the patient(Kennedy, Aghababian et al. 1996; Iserson and Moskop 2007; Jenkins, McCarthy et al. 2008). As the accurate assessment of patient injuries can be problematic in an emergency situation, patients are occasionally misdiagnosed and sent to health facilities that are not equipped to treat their injuries. This process is referred to as undertriage. Overtriage, on the other hand, occurs when patients with minor injuries are sent to facilities capable of treating critically wounded patients. Although undertriage can cause patients to go without proper treatment, overtriage can also be detrimental in a mass casualty incident where resources are scarce (Cooper and Yarbrough 1995; Plani 2009). In such cases, an influx of overtriaged patients can cause critically injured patients to go without care unnecessarily. In fact, some evidence shows that overtriage during a mass casualty can be linked to the loss of salvageable lives (Frykberg and Tepas 1988).Much of the research in this area has examined ways for improving triage results both in prehospital and hospital triage.

Another focus within triage research is on the classification of triage methods and systems and the conditions under which triage takes place. Because triage on the battlefield (during a war) requires different techniques than triage undertaken during a chemical or biological incident, guidelines are available to assist practitioners in modifying known systems of triage, like START and SAVE, to meet these different conditions (Cone and Koenig 2005; Baker 2007). Within North America, the Simple Treatment and Rapid Transport (START) system is used for primary triage (deciding where to evacuate patients) while the Secondary Assessment of Victims (SAVE) system is used for secondary triage (prioritizing patients within the hospital) (Benson, Koenig et al. 1996; Asaeda 2002).

1.4.3 Hospital Surge Capacity

Defined as a hospital's ability to accommodate a sudden extreme increase in the number of patients, the ability to quantify the 'surge capacity' of a particular hospital is pivotal in deciding where to evacuate patients (Davis, Poste et al. 2005; Centers for Disease Control and Prevention 2010). In order to estimate hospital surge capacity, health authorities generally rely on an examination of regular daily surge periods, however models simulating surge capacity have also been used for this purpose (Davis, Poste et al. 2005; Barbisch and Koenig 2006; Nager and Khanna 2009).

In the US, hospital surge capacity benchmarks are set by the Health Resource and Service Administration (HRSA) as a means to prepare for a mass casualty or disaster. The HRSA regional bench mark for burns or trauma is set at 50 beds per million within a 24 hour period. In various other countries, surge capacity benchmarks require a specific percentage increase in patient care capacity at each hospital (Schultz and Koenig 2006; Agency for Healthcare Research and Quality 2010).

In extreme situations, like those encountered within a mass casualty or large scale disaster, unusual means are sometimes used to expand the maximum capacity of a hospital. An example of this is the creation of makeshift treatment areas within non-medical spaces (e.g. cafeteria, auditorium, etc.) in order to provide basic medical care during a surge. Changes in hospital practice, particularly secondary triage, can also have a positive effect on surge capacity (Hick, Hanfling et al. 2004; Kaji, Koenig et al. 2006).

Additional staffing, equipment/supplies and infrastructure have been identified as the three factors critical to the management of surge capacity and the maximization of hospital bed capacity. During a surge there is a need for extra personnel to deliver care to the increased numbers of patients entering the hospital. Extra equipment, pharmaceutical and surgical supplies are also necessary. With respect to infrastructure, there is a need both for additional physical space to shelter patients and for an organizational communication system which has the capacity, tools and knowledge to expand and manage a surge both within the hospital and within the surrounding community (Barbisch 2005; Barbisch and Koenig 2006; Agency for Healthcare Research and Quality 2010). Accurate triage and the proper preparedness and management of mass casualty are also commonly identified as key elements in effectively enhancing surge capacity.

1.5 Literature Review

1.5.1 Models within mass casualty

In order to more effectively examine systematized responses to mass casualty incidents, researchers have also created models that enable real time simulation. Such models are aimed at those in decision-making or management roles and are intended to assist in the management of such incidents. These models tend to focus on mass casualty processes from a macro perspective. For example, a model of this type will simulate various stages of a mass casualty, like EMS response, evacuation or hospital response, but will not simulate the processes within each of these stages (Fawcett and Oliveira 2000; Hupert, Mushlin et al. 2002; Hoard, Homer et al. 2005).

A second type of modeling is that which aims to model a certain process in detail. Such processes might include surge capacity and/or a hospital's ability to admit patients under varying conditions. A model of surge capacity, for example, would evaluate all the processes that occur within surge capacity including triage, allocation of patients to beds and the flow of patients within the hospital (Hirshberg, Stein et al. 1999; Morin, Jenvald et al. 2000; Vardi, Levin et al. 2002).

Though spatial modeling and the geographic location of patients have been given very little attention within the field of mass casualty, some spatial modeling has been done in the field of emergency services.

1.5.2 Spatial Modelling in EMS

Most spatial modeling for emergency services focuses on the optimization of ambulance locations in order to maximize coverage (Toregas, Swain et al. 1971; Church and ReVelle 1974; Hogan and ReVelle 1986; Brotcorne, Laporte et al. 2003). These models have evolved from the simple static models first developed 30 years ago so that they now incorporate dynamic circumstantial changes. For example, such models can determine how best to fill the gap in coverage that is created when an ambulance within a particular geographical catchment is dispatched. In recent years, there have been a handful of attempts to optimize ambulance response times using models that incorporate dynamic traffic changes (Derekenaris, Garofalakis et al. 2001; Gendreau, Laporte et al. 2001; Huang and Pan 2007). Dynamic modeling of this type, while still in its infancy, is an emerging area of EMS research.

Static Location Optimization Models

The first location models were simple, intended either to maximize the population covered by a set number of ambulances or to determine the minimum number of ambulances required within a certain geographical area in order to meet a certain level of coverage (Brotcorne, Laporte et al. 2003). Used primarily for planning purposes, such models provided simple, practical solutions which, when implemented, saved both money and lives (Toregas, Swain et al. 1971; Brotcorne, Laporte et al. 2003). These static models, known as location set covering models (LSCM), consisted of a series of 'demand' points representing areas requiring ambulance services (Toregas, Swain et al. 1971). The locations of ambulance facilities were determined with the use of these models, and were distributed so as to provide optimal coverage to the demand points using driving time calculation. As the demand points used with these models were not weighted, each demand point had the same likelihood of receiving coverage (Brotcorne, Laporte et al. 2003). A more advanced static model, incorporating demand points weighted by population covered, and known as the Maximal Covering Location Problem (MCLP), was later developed. This model provided more coverage in areas where population counts were higher, and generally resulted in a reduction in the number of ambulances needed within the same geographic area (Church and ReVelle 1974; Eaton, Daskin et al. 1985; Pirkul and Schilling 1988). The principal problem with the static models was their inability to respond to changes in coverage within a particular area as a result of ambulances being dispatched.

Optimizing Ambulance Location - Beyond Static Modelling

In order to deal with the flaws in the static models, a more advanced set of models, known as BACOP (Backup Coverage Problem) and DSM (Double Standard Model), were developed (Hogan and ReVelle 1986; Gendreau, Laporte et al. 1997). These newer models were designed to overlap the coverage provided by each ambulance, such that a particular ambulance would provide primary coverage to its own catchment and secondary coverage to the catchment of a neighbouring ambulance. In this way, gaps brought about by the dispatching of ambulances within a particular catchment, could be covered by an ambulance in a neighbouring catchment, for the duration of the incident (Gendreau, Laporte et al. 1997; Gendreau, Laporte et al. 2001; Brotcorne, Laporte et al. 2003). As this multiple coverage model could not always be implemented (due to financial constraints), a second, and more sophisticated model, was created to allocate coverage based on areas of higher demand. Within this model, areas of high demand might receive both primary and secondary coverage before an area of lesser demand received primary coverage. While this compromised the service provided within certain areas, it also maximized the utilization of ambulances within a given population. These types of models could be modified, based on geographic boundaries and population distribution, to provide different levels of coverage and to adapt to situations where one or more ambulances were in use (Hogan and ReVelle 1986; Brotcorne, Laporte et al. 2003).

The above location models were deterministic in nature and did not account for randomization (ReVelle and Hogan 1989). Other sets of models have been developed that determine levels of coverage by using probability to estimate demand, and therefore ambulance availability (Goldberg, Dietrich et al. 1990; Marianov and Revelle 1994). The first probabilistic model developed was the Maximum Excepted Covering Location Problem Formulation (MEXCLP) model (Daskin 1983). This model looked at a variable known as the 'busy fraction', which describes the probability of an ambulance being unavailable to answer a call within the desired traveling time. It is calculated by estimating the number and duration of past calls within a given time period and dividing this total by the total number of ambulances available. The model then aims to spatially position the ambulances so as to cover the greatest number of calls within the desired travel time for each ambulance. Most of the probabilistic models rely on the busy fraction for their calculations and assume that all ambulances operate independently of one another (Brotcorne, Laporte et al. 2003). A more advanced version of the MEXCLP model incorporates simulation. The simulation shows the probability of an ambulance reaching each of the demand points from a preferred facility site by combining the probability of that facility being available within the desired driving time. The total probability for each demand site can then be visualized (Goldberg, Dietrich et al. 1990). A TIMEXCLP is an MEXCLP model with the ability to add different travel times, representing traffic patterns at different times of the day, to the model. The TIMEXCLP model was later utilized by Repede and Bernando (1994) when designing a decision support system for the location of EMS vehicles in Kentucky (Repede and Bernardo 1994). In fact, several variations of the MEXCLP model have been developed, including models that did not assume the independent operation of ambulances or a uniform 'busy factor' for all demand surfaces (ReVelle and Hogan 1989; Ball and Lin 1993; Marianov and Revelle 1994; Mandell 1998). As computer processing power increased, these probabilistic models evolved into models of a more dynamic nature.

Dynamic Models

The static models described previously were used primarily for planning purposes and did not address the fact that ambulance locations change continually throughout the day. In reality, the number and location of available ambulances must be constantly updated in order to maintain maximum levels of coverage. Only a handful of models have been built to accommodate real time changes in ambulance location (Gendreau, Laporte et al. 2001; Rajagopalan, Saydam et al. 2008). The first was a model developed by Gendreau et al (2001) which allowed for the reallocation of ambulances within the fleet every time a call was made (Gendreau, Laporte et al. 2001). The model is a very complex one, as it is programmed to accommodate realistic variables like repeated and or long trips, and the dispatching of an ambulance near the end of its shift when the crew is being replaced. Its principal objective is to maximize fleet double coverage (primary and secondary coverage) by reallocating ambulances after each ambulance dispatch. The model uses parallel computing to support the heavy computation required for it to operate (Brotcorne, Laporte et al. 2003). It also uses a technique that pre-calculates scenarios during non-busy periods in order to save computation time when a call does occur. In a simulation, using real data, that took place in the city of Montreal, 98% of urgent calls were answered within the required 7 minute period. A similar model, which aimed to increase model response times, was constructed in 2006 (Brotcorne, Laporte et al. 2003; Rajagopalan, Saydam et al. 2008).

Optimizing Ambulance Routing to an Incident

Another type of EMS related spatial modeling, dealing with optimal ambulance routing, has emerged in recent years. To date, only a few models for the purpose of EMS vehicle routing have been created. This is due in large part to the computational complexity of incorporating live data related to traffic changes and to the difficulty of processing such large amounts of data in a very short period of time. Moreover, these models are not always effective in an urban environment, in which driving time to an incident is generally only a few minutes in total. In such cases, depending, of course, on the level of congestion present, it is often not worth rerouting the vehicle.

In a paper describing their own ambulance routing optimization model, Dereknaris et al (2001), discuss the advantages and disadvantages of incorporating real-time traffic data. Using GIS and GPS to obtain ambulance locations and traffic data from different sources, the Dereknaris model relies on the dispatcher to run the model after first geocoding the incident locations. The dispatcher uses the model to calculate the optimal route from the ambulance to the incident location and then communicates this information to the ambulance. In this case the authors were unable to provide optimal routing from the incident to the appropriate hospital in real time given the size and complexity of the Athens road network. This is the only known attempt to model routing from an incident location to a hospital. It was discussed only briefly in the Dereknaris paper because, as mentioned, the attempt was hindered by the computer's inability to run the model (Derekenaris, Garofalakis et al. 2001).

A more advanced model, created by Huang and Pan (2007), was tested on tow trucks in a suburban area of Singapore (Huang and Pan 2007). Huang and Pans IRMOM (incident response management model) model integrates TransCAD, a GIS tool designed for transportation applications, PARAMICS, a traffic simulation tool, and LINDO, a tool which calculates driving times and outputs these for visualization through TransCAD. The model allows users to input variables like incident location, time and priority before executing the scenario. The model then outputs, for each of the response units in the study area, the best route to the incident location. Although this model is very sophisticated, it is does not incorporate real time traffic data but rather a simulation of real time traffic data. It has also not been tested on complex and dense road networks like those found in large North American or European cities (Huang and Pan 2007).

Although the spatial models described thus far have contributed to developments in EMS routing and coverage, none have specifically addressed evacuation prioritization within a mass casualty situation.

1.5.3 Spatial Decision Support Systems

Combining geographic information systems (GIS) with decision support systems (DSS), Spatial Decision Support Systems (SDSS) were first introduced in the mid 1980's (Shim, Warkentin et al. 2002; Keenan 2004). Decision support systems consist of distinct data management, model and interface components. Spatial Decision Support Systems add the visualization of spatial attributes to the DSS, while Geographic Information Systems enable spatial data to be stored, manipulated and displayed. SDSS gained popularity in the 1990's when advances in computer technology enabled more efficient processing of the large and complex datasets on which these systems are based. SDSS provide the ability to solve and simplify complex spatially-oriented problems (Armstrong, Rushton et al. 1991; Densham 1991; Crossland, Wynne et al. 1995; Loucks 1995).

The most advanced application of SDSS has been within the context of route planning and optimization. The incorporation of real time traffic data requires exceptionally powerful computer processing and very advanced SDSS. As mentioned earlier, attempts to model route optimization for emergency service vehicles have thus far been hindered by the inability to efficiently calculate real time traffic information. However, other route optimization applications have been developed. Used primarily for planning purposes, these models have been adopted by several different industries, including trucking and waste collection. SDSS models are intended to optimize routing between two or more locations using several well-defined parameters. For example, a truck routing SDSS might enable the user to insert truck and cargo type in addition to all truck and loading stops throughout the day before outputting the optimal route for the driver. These sophisticated applications combine analysis of the road network with several other variables in calculating the optimized route. Although they do not react to dynamic changes like the EMS models, they are similar in that they consider several variables in the route calculation. The use of these models has been shown to directly reduce organizational costs in terms of fuel, time and vehicle use (MacDonald 1996; Chang and Lu 1997; Tarantilis and Kiranoudis 2002; Butler, Herlihy et al. 2005; Ray 2007).

1.5.4 Web Based SDSS

In recent years a new kind of SDSS has emerged; one that relies on the web as a platform for interaction with the user. Made possible by increases in the speed of data transfer between client and server computers, web based SDSS enable greater information sharing and heightened use by non experts (Rinner 2002). It also enables users to create their own content and actively interact with other users via web 2.0 technology (Schuurman, Leight et al. 2008). Web-based SDSS provide the general population with access to services that were previously available only to professionals, thereby reducing organizational reliance on in-house GIS applications. Web based SDSS also allow for the building of customized GIS applications that can be used with a remote server. These applications are platform independent and therefore more widely accessible. They are also purpose built, with tailored commands and functions making the application simpler to operate and understand than a full-blown desktop application. The resulting reductions in training, technical support and hardware costs make SDSS an attractive alternative to the robust desktop systems currently in place (Sugumaran 2005; Bhargava, Power et al. 2007).

To date, no known web-based SDSS have been developed for EMS usage. This may be because such applications are not used by the general public, because interactions with a remote server are sometimes unreliable, something that is particularly undesirable in an emergency situation, and/or because web-based applications are typically slower than desktop models.

1.5.5 Mass Casualty Evacuation Priorities

Although MCI research has given little attention to evacuation priorities, patient prioritization and evacuation has been a focus within trauma systems research. In the case of trauma systems research, the research has centered on comparisons of patient outcomes in inclusive and exclusive trauma systems (Nathens, Maier et al. 2003; Utter, Maier et al. 2006). One of the most comprehensive studies of MCI evacuation was conducted by a team of Israeli trauma researchers. Examining the evacuation priorities utilized in 33 Israeli mass casualty incidents between 2000 and 2002, Einav et al.(2004) provided a detailed analysis of evacuation time and hospital prioritization, while also timing the arrival of emergency personnel at the incident locations. Their results demonstrated that most patients were evacuated to the hospital closest to the scene, rather than to a level 1 trauma hospital, regardless of the severity of their injury. Their results support the notion that patient outcomes are improved in inclusive trauma systems where patients can be evacuated to the nearest hospital and then transferred between hospitals as required. This practice allows for patient resurrection and also prevents overcrowding within a particular hospital (Einav, Feigenberg et al. 2004; Pinkert, Leiba et al. 2007; Schwartz 2007).

1.6 Thesis Outline

This thesis is comprised of four chapters. The bulk of the thesis (Chapters 2 and 3) is comprised of two studies that have been submitted for publication (separately) in two different peer-reviewed journals.

Chapter 1 contains a review of concepts central to the research and is intended to introduce the reader to current issues concerning mass casualty research. This includes mass casualty and emergency services modeling and SDSS.

Chapter 2 describes the building of the core functionalities of the proposed model, including a description of the data and technology used therein. The development of the model at this stage did not include the ability to provide real time capacity information. This functionality was added and later on and is described in chapter 3. This chapter also compares and validates the model driving times against actual ambulance driving times.

Chapter 3 uses a simulation to assess the applicability of the model. Using information, such as patient counts and flow rates, from the 2005 London bombings, this chapter illustrates the use of the model with two simultaneously occurring mass casualties. The model also incorporate within it real time hospital capacity functionality.

Chapter 4 reflects on the purpose, methods, results, and recommendations of the thesis. The overall contributions are described, followed by a discussion of potential future directions for further developing the model.

2: CHAPTER 2
Mass Casualty Modelling: A Spatial Tool to Support Triage Decision Making

2.1.1 Background

During a mass casualty incident, evacuation of patients to the appropriate health care facility is critical to survival. Despite this, no existing system provides the evidence required to make informed evacuation decisions from the scene of the incident. To mitigate this absence and enable more informed decision making, a web based spatial decision support system (SDSS) was developed. This system supports decision making by providing data regarding hospital proximity, capacity, and treatment specializations to decision makers at the scene of the incident.

2.1.2 Methods

This web-based SDSS utilizes pre-calculated driving times to estimate the actual driving time to each hospital within the inclusive trauma system of the large metropolitan region within which it is situated. In calculating and displaying its results, the model incorporates both road network and hospital data (e.g. capacity, treatment specialties, etc.), and produces results in a matter of seconds, as is required in a MCI situation. In addition, its application interface allows the user to map the incident location and assists in the execution of triage decisions.

2.1.3 Results

Upon running the model, driving time from the MCI location to the surrounding hospitals is quickly displayed alongside information regarding hospital capacity and capability, thereby assisting the user in the decision-making process.

2.1.4 Conclusions

The use of SDSS in the prioritization of MCI evacuation decision making is potentially valuable in cases of mass casualty. The key to this model is the utilization of pre-calculated driving times from each hospital in the region to each point on the road network. The incorporation of real-time traffic and hospital capacity data would further improve this model.

2.2 Introduction

On July 7th, 2005, a series of terrorist attacks shook the London transit system (Lockey, MacKenzie et al. 2005). Four bombs exploded almost simultaneously in a coordinated attack that left the city in a state of chaos (Aylwin, König et al. 2006). Based on the sheer number of casualties, the incident has been described as the largest mass casualty incident in the United Kingdom since World War Two. Altogether, 775 people were injured in the attack, of which 56 died and 55 were critically injured. Casualties were divided amongst six hospitals (inclusive) within the city, based on hospital proximity, capacity and capability (Aylwin, König et al. 2006).

The following paper describes a spatial decision support system (SDSS) intended to help determine where best to evacuate patients during a mass casualty incident (MCI) of this type.

Mass casualty incidents are those that, by the sheer number and severity of casualties, overwhelm the health care capacity within a given community (Hammond 2005; Shoher, Chang et al. 2006; Lennquist 2007). This definition emphasizes the crucial role played by triage and trauma centers in maximizing capacity during a mass casualty incident (Frykberg 2004). A concept that originated on the battlefield, triage, meaning 'to sort' in French, is one of the critical factors in the effective management of mass casualty incidents and refers to the process of prioritizing medical care based on the medical condition of the patient (Kennedy, Aghababian et al. 1996; Iserson and Moskop 2007; Jenkins, McCarthy et al. 2008).

Intended to simplify and make evidence-based decisions concerning the evacuation of critically injured patients from an MCI location, this SDSS provides the information required by emergency service personnel at MCI location to make decisions in what is typically, a highly stressful and often chaotic situation. In addition to providing, within a matter of seconds, critical information describing hospital driving time/proximity, trauma level and bed capacity, the model is also useful within a planning context. For example, the model can be used to examine proposed locations for large scale events, conferences, etc. in relation to health care facilities or to help to determine where to position a mobile health facility in relation to the event.

Spatial models have been used within emergency services (EMS) for some time. Location allocation models, for example, are used to position facilities so as to optimize services to customers. In EMS, such models are focused on the optimization of ambulance locations in order to maximize coverage(Toregas, Swain et al. 1971; Church and ReVelle 1974; Hogan and ReVelle 1986; Brotcorne, Laporte et al. 2003). These models have evolved from the simple static models first developed 30 years ago to incorporate dynamic circumstantial changes. For example, such models can determine how best to fill the gap in coverage that is created when an ambulance within a particular geographical catchment is dispatched. In recent years, there have been a handful of attempts to optimize ambulance response times using models that incorporate dynamic traffic changes (Derekenaris, Garofalakis et al. 2001; Gendreau, Laporte et al. 2001; Huang and Pan 2007). Advances in computer technologies that support decision making have made this process easier.

Combining geographic information systems (GIS) with decision support systems (DSS), Spatial Decision Support Systems (SDSS) were first introduced in the mid 1980's (Shim, Warkentin et al. 2002; Keenan 2004). Decision support systems consist of distinct data management, model and interface components. Spatial Decision Support Systems add the visualization of spatial attributes, while Geographic Information Systems enable spatial data to be stored, manipulated and displayed. SDSS provide the ability to solve and simplify complex spatially-oriented problems (Armstrong, Rushton et al. 1991; Crossland, Wynne et al. 1995; Loucks 1995). In recent years a new kind of SDSS has emerged; one that relies on the web as a platform for interaction with the user. Made possible by increases in the speed of data transfer between client and server computers, web based SDSS enable greater information sharing and heightened use by non experts (Rinner 2002). Web based SDSS also allow for the building of customized GIS applications that can be used with a remote server. These applications are platform independent and therefore more widely accessible. They are also purpose built, with tailored commands and functions making the application simpler to operate and understand than a full blown desktop application (Rinner 2003; Sugumaran 2005; Bhargava, Power et al. 2007). To date, no known modeling of MCI evacuation priorities has been undertaken and no emergency service models have been created to aid in evacuation prioritization. While there have been a few attempts to model optimal EMS routing to the scene of an incident, there was only one known attempt to model the return (Derekenaris, Garofalakis et al. 2001; Huang and Pan 2007). Drawing inspiration from the EMS models described above, the SDSS proposed within this paper also incorporates the use of GIS in the calculation of road network driving times.

2.3 Methods

2.3.1 Data

Two sets of data were used in constructing this model: road network data and hospital location data. The road data for metro Vancouver, obtained through GIS Innovations (GISInnovations 2009), is highly suitable for calculating travel time as it incorporates both speed limits and travel impedances (i.e. stop signs, traffic lights, etc.) which, in turn, allow for accurate travel time calculation. The data also provides the ability to control travel and impedance times. This is important, as travel times for an ambulance will differ from that of a regular vehicle. The fact that this data enables control of such variables heightens the accuracy of the results. The road network dataset used in this study excluded back roads and logging roads in order to focus on the more populated sections of the study area. Excluding these smaller roads also helped to reduce the database size. Elevation-related information was also excluded from the dataset. This may have slightly impacted the accuracy of the driving time calculations.

The second set of data utilized in this study is comprised of the locations of participating hospitals within the metro Vancouver region. In addition to geocoded hospital locations, the hospital dataset also attaches attributes describing the hospital's capacity to receive patients in the case of a mass casualty incident and the type of treatment a given hospital is able to provide (Table 1). For trauma services, the range of services includes ICU, neurosurgery, orthopedics and plastic surgery. The hospitals are represented as a set of GIS point features and are geocoded as close to the main emergency room access as possible. As large hospitals can span several street blocks, geocoding the ER location rather than the hospital centroid can produce more accurate driving time results.

Level of care	
1	*Central role in the provincial trauma system, and majority of tertiary/quaternary major trauma care in the system. Academic leadership, teaching, research program*
2	*Provides care for major trauma. Some trauma training and outreach programs. Similar to level 1 without academic and research programs*
3	*Provides initial care for major trauma patients and transfers patients in need of complex care to level I and II trauma centers.*
4	*Major urban hospital with a nearby major trauma centre (level I-3). Does large volume of secondary trauma care. Bypass and triage protocols are in place diverting major trauma patients to level 1 and 2 centers.*

Table 2-1: Trauma center designation in Canada (Hameed, Schuurman et al. 2010).

In order to obtain results in a more immediate fashion, this model utilized pre-calculated driving times from each location on the road network to each hospital in the study area. Before pre-calculating the driving times, the data first had to be discretized to a length which would minimize the effect on actual driving time calculation. By restricting the length of the discretized road segments to a maximum of 200m, it was determined that accurate driving times could be achieved without negatively affecting either the results or the size of the road dataset. The same road data used for the driving time calculation was also used to create the road segments. Close examination of the GIS Innovations (GISInnovations 2009) data indicated that the road segments within the data varied drastically in length, with segments both much smaller and much larger than 200m. After several experiments, it was found that leaving all road segments below 200m unchanged and subdividing all road segments larger than 200m to the 200m maximum worked most effectively. The 200m street segments provided accurate driving times while also keeping the size of the database manageable. The resulting dataset contains road segments of varying lengths, with no segment larger than the 200m maximum.

In order to calculate driving time from each road segment to each hospital, each road segment was converted into a centroid. The ODMatrix function within ESRI ArcGIS network analyst was then used to calculate driving time to each hospital. The ODMatrix function calculates the shortest driving time from each point of origin to each destination on the road network producing a 'drivingTime' table which contains a unique ID for each centroid plus the driving time in minutes to each hospital (ESRI 2006). In order to attain greater accuracy, an impedance time value was obtained from experienced paramedics and assigned to both stop signs (5 second) and traffic lights (10 seconds). The table also produces a hospital unique ID for each destination hospital. Once this table was created, the centroid ID was reassigned to its road segment so that the user could click on the road segment and retrieve its unique ID (Figure 1). The road data set consisted of a road segment shapefile within which each segment was related to the driving timetable through a one-to-many relationship.

The final step in the data preparation was to create the hospital data list. This was a relatively simple task, as all the information was readily available, the locations were known and only a relatively small number of hospitals were involved in the study. As part of the data preparation, each hospital was given a unique ID corresponding to the driving time table with a many-to-one relationship.

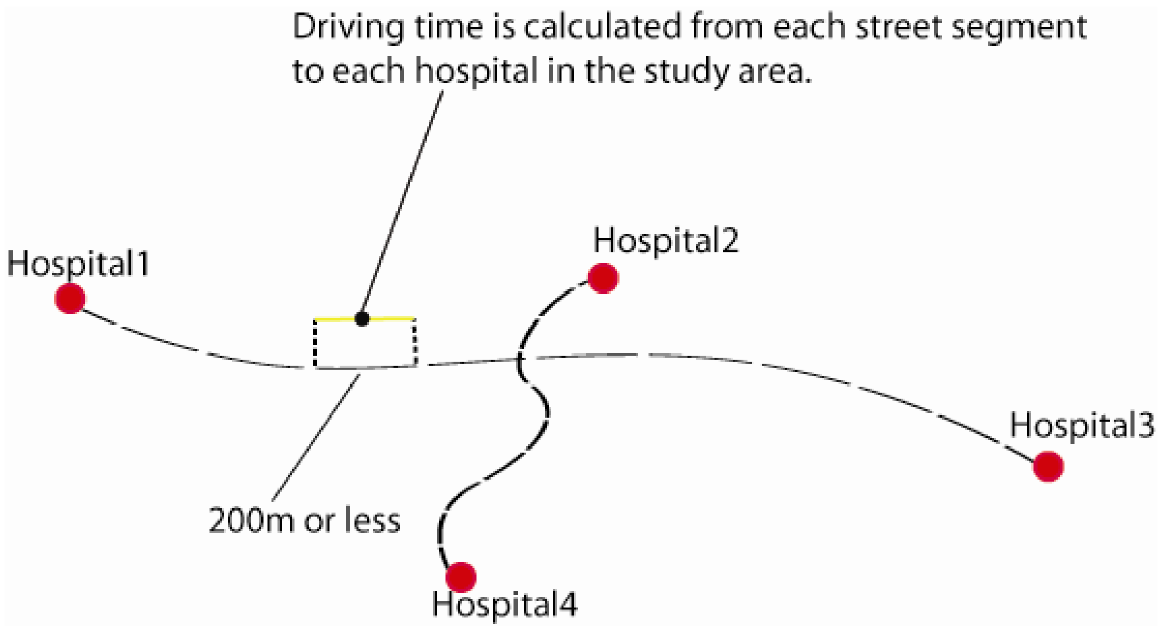

Figure 2-1: **Shows the method of pre calculating driving times to each hospital in the study area. The road network is divided into segments 200m or less in length. Driving time to each hospital is then calculated from each road segment in the study area.**

2.3.2 Model Construction

The construction of the model was divided into two distinct parts: creation of the mapping interface (the SDSS) and creation of a mechanism to analyze and process the data (model). The mapping interface was designed to allow the user to zoom to a location and to click on a road segment and insert a location into the map. In order to facilitate this, the 200m segmented road data was first uploaded into ArcGIS server. A block of code was then written to allow users to click on a road segment, insert an MCI location and retrieve the unique ID of the road segment. Once retrieved, the unique ID is used to obtain the driving time to each hospital from the pre calculated driving time table. This portion of the model was constructed using ArcGIS server API, as it provides a rich set of functionalities and tools to interact with the road data and allow developers to build complex web-based mapping applications.

The second aspect of constructing the model involved creating a mechanism to join the unique ID from each road segment to the pre calculated driving time table, establishing a database relationship between the driving time table and the hospital table, and analyzing and visualize the resulting data (Figure 2). For this purpose, VB.NET (Microsoft 2001) was utilized as the server side scripting language while javascript was used as the client side scripting language. VB.NET enables database interaction and provides a set of decision making tools for the analysis and visualization of results using tables and graphs. More specifically, VB.NET is used to compile the data and display the results based on the user's input(Microsoft 2001). The entire model, including mapping and analysis, was built in Visual Web Developer (VWD) 2008 express edition (Microsoft 2008).

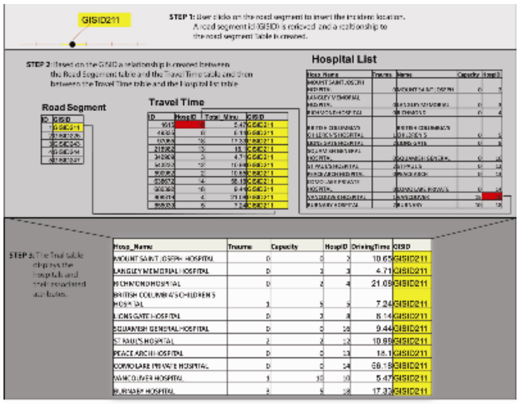

Figure 2-2: **Illustrates creation of hospital table and its associated attributes.**

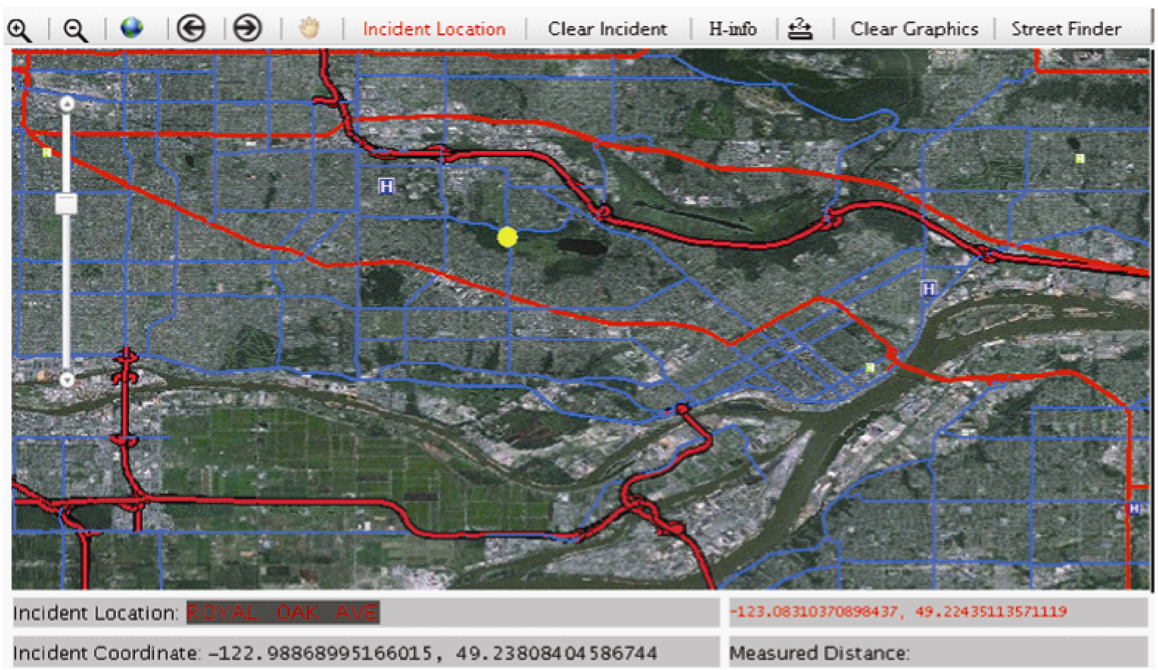

Figure 2-3: **A digital map indicates the location of the MCI and surrounding hospitals**

2.4 Results

The database becomes active when the user enters the web site and a connection to the hospital data table is established as the page loads. Once this takes place, the user can modify the default hospital capacity and determine which hospitals should be included in the analysis. The user then needs to insert the MCI location into a high resolution map (Figure 3) and enter additional information like the incident reference location. After an MCI location is inserted into the map, the model is ready to be executed. Upon running the model, a new results page opens listing each hospital, its associated attributes and its driving time from the MCI location. The results page provides a visual representation of the analysis, using both tables and graphs.

In order to test the model, a simulated MCI was created within the study area, using casualty counts from the 2005 London bombings. Using the King's Cross counts, where 10 critically injured patients were evacuated, an incident location was inserted at Broadway sky train station, one of Vancouver's busiest train stations. Figure 4 shows the results page produced by the simulation. Driving times to each of the hospitals in the study area are shown along with hospital capacity and trauma level. The results indicate that patients should be distributed between Vancouver General Hospital and Royal Columbian Hospital. In addition to driving times to trauma hospitals, the proximity to the nearest non-trauma hospital (depicted as trauma level 9) is also important as it provide an option in cases where the trauma hospitals become overloaded.

Hospital	DrivingTime	Capacity	Trauma
VANCOUVER GENERAL	6.87	10	1
ROYAL COLUMBIAN	15.37	5	1
MOUNT SAINT JOSEPH	3.85	1	9
BURNABY	8.69	1	9
ST PAULS	9.1	1	9
LIONS GATE	13.71	2	9
SAINT MARYS	18.98	1	9
RICHMOND	20.34	1	9
DELTA	23.11	1	9
SURREY	27.91	1	9

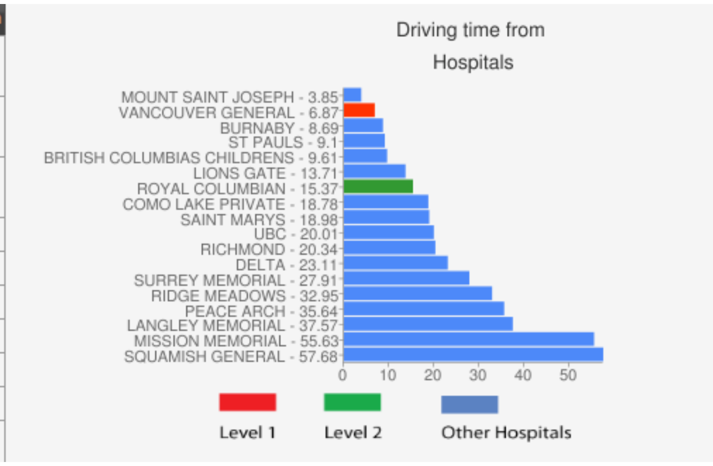

Figure 2-4: Shows hospital driving times created during a simulation. The table provides information regarding the proximity of hospitals to the MCI, their capacity and trauma level. Trauma level 1 hospitals are preferred when located in close proximity to the MCI location. However, in cases where Trauma level 1 hospitals are full or busy, the nearest non-trauma hospital will be utilized.

2.4.1 Driving Time Validation

Figure 5 and table 2 illustrate differences between the model's driving times and actual ambulance driving times collected from two ambulance stations within the metro Vancouver area. The driving times that were collected were for critically injured patients only. One ambulance station was located within an urban setting while the other was located in suburban Metro Vancouver. After filtering the data to show only trips occurring between 7pm and 7am, and 12 to 3pm, the 132 ambulance trips showed larger variability in the ambulance driving time compared with the model driving time. The graph shows that the model underestimates and overestimates driving time in both long and short ambulance trips. There are several reasons that this may have occurred. First, the model driving times were rounded to the minute in order to be able to compare them to ambulance driving times (ambulance results were logged in minutes). Second, ambulance driving time records were taken from the ambulance paper log and there is no way to track at which point in the ambulance trip the start and end time of the trips were entered into the paper sheet. Both of these issues may drastically affect the results, particularly when the trip time is short. These unavoidable inconsistencies may partially explain the variability scatter in the graph in Figure 5.

The table below shows nine incidents where ambulance trips started and ended in exactly the same location. In this case, patients were being transferred from a non-trauma hospital to a major trauma hospital. The model time calculation was 13 minutes while most of the actual ambulance driving time ranges from 8 to 13 minutes with one trip as an outlier at 27 minutes. The table results illustrate the variability between trips from and to the same locations. The results from the table illustrate the relatively limited variability of ambulance driving time compared to our model.

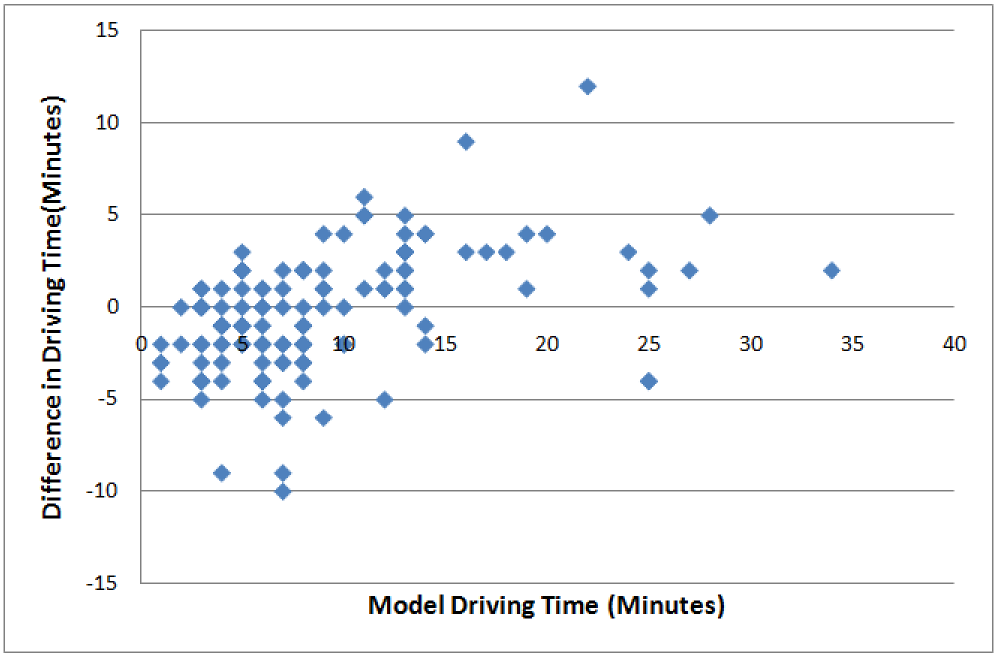

Figure 2-5: Shows how actual ambulance driving times deviate from driving times within the model

Origin	Destination	ModelTime(Min)	AmbulanceTime(Min)
SMH	RCH	13	10
SMH	RCH	13	12
SMH	RCH	13	11
SMH	RCH	13	12
SMH	RCH	13	8
SMH	RCH	13	27
SMH	RCH	13	10
SMH	RCH	13	13
SMH	RCH	13	9
SMH	RCH	13	10
SMH	RCH	13	11

Table 2-2: Shows comparison between model driving time and actual ambulance driving time for nine ambulance trips which had the same origin and destination.

2.5 Conclusion

The response to a MCI must be both swift and precise if it is to be effective. As a result, dynamic decision-making is of critical importance (Gonzalez and Brunstein 2009). To be useful in this context, MCI modeling must produce results within an extremely short period. Although the proposed model provides the basic information required for evidence-based decision-making, improvements can still be made, particularly in regard to the provision of real time hospital capacity and traffic data. Real time hospital capacity can be obtained by creating a utility that will enable hospitals to update capacity in the hospital database as soon as a mass casualty is declared. The model can then connect to the hospital database to retrieve the capacity. In addition, the model allows updates in hospital capacity as patients are evacuated from the scene of the incident to a given hospital. Incorporation of real time hospital capacity into the model is currently in development. Unfortunately, incorporating real time traffic data is more complicated, as to do so would significantly extend the time required for computer data processing (Derekenaris, Garofalakis et al. 2001; Ghiani, Guerriero et al. 2003). Although the model described in this study was able to avoid significant processing delays by utilizing pre-calculated driving times from each location on the road network to each hospital in the study area, the use of pre-calculated driving times also introduces some limitations. It does not, for example, allow for the input of travel impedances, like street closure as a result of the MCI, like bridge closures, or construction, into the calculation. Table 2, which compares model travel times with actual ambulance travel times, highlights the need to implement travel time calculations in real time while also incorporating real time traffic data. Out of the nine identical ambulance trips that were recorded, one trip clearly took much longer than the others. While the reason for this particular delay is unknown, a real time traffic data and driving time calculation might have suggested a different route if a traffic problem were the cause.

During an MCI, decisions regarding the evacuation of patients are based on an evaluation of injury type and severity, in relation to hospital proximity and capacity. The web based model proposed within this study is intended to provide evidence-based hospital and driving time information in a timely manner to assist in the onsite management of MCI incidents.

3: CHAPTER 3
Mass Casualty Modelling: Assessment of Patient Evacuation through Simulation

3.1.1 Background

In a mass casualty situation, evacuation of patients to the appropriate health care facility is of critical importance. The pre-hospital stage of a mass casualty incident (MCI) is typically chaotic, characterized by dynamic changes and severe time constraints. As a result, those involved in the pre-hospital evacuation process must be able to make crucial decisions in real time. This paper presents a model intended to assist in the management of mass casualty incidents. This model is an extension of a model created earlier (Chapter2) as it adds real time hospital capacity functionalities.

3.1.2 Methods

Road network data and hospital location data were used to pre-calculate road travel times from each point on the road network to all Level 1 to 3 trauma hospitals. Hospital capacity data was obtained from hospitals and was updated by tracking patient evacuation from the MCI locations. In combination, these data were used to construct a web-based simulation model for use by emergency response personnel.

3.1.3 Results

The model provides information critical to the decision-making process within a matter of seconds. This includes driving times to the nearest hospitals, the trauma service level of each hospital, the location of hospitals in relation to the incident, and up to date hospital capacity.

3.1.4 Discussion

The dynamic and evolving nature of mass casualty incidents requires that decisions regarding pre-hospital management be made under extreme time pressure. This model provides tools for these decisions to be made in an informed fashion with continuously updated hospital capacity information. In addition, it permits complex MCI simulation for response and preparedness training.

3.2 Introduction

On July 7th, 2005, a series of terrorist attacks shook the London transit system (Lockey, MacKenzie et al. 2005). Four bombs exploded almost simultaneously in a coordinated attack that left the city in a state of chaos (Aylwin, König et al. 2006). Based on the sheer number of casualties, the incident has been described as the largest mass casualty incident in the United Kingdom since World War Two. Altogether, 775 people were injured in the attack, during which 56 died and 55 were critically injured. Casualties were divided amongst six hospitals within the city, based on hospital proximity, capacity and capability (Aylwin, König et al. 2006). The principle challenge in such situations is to transfer patients to the appropriate level of care in the most expeditious manner. The pre-hospital stage of a mass casualty incident (MCI) is typically chaotic, characterized by dynamic changes and severe time constraints. As a result, those involved in the pre-hospital evacuation process must be able to make crucial decisions in real time and communicate them effectively (American College of Surgeons 2003; Gonzalez and Brunstein 2009).

This paper presents a model intended to assist in the management of mass casualty incidents. Designed to allow first responders to more easily and accurately determine the appropriate hospital for the evacuation of patients from a mass casualty, the model provides information critical to the decision-making process within a matter of seconds. This includes driving times to the nearest hospitals, the trauma service level of each hospital, the location of hospitals in relation to the incident, and up to date hospital capacity. To demonstrate the applicability of this model, casualty counts and incident characteristics from the 2005 London bombing were used as simulation data and applied to two locations in the study area. In order to make the simulation as comparable as possible, the locations were chosen based on similarities in their built environment.

3.2.1 Mass Casualty and Disaster Management

The chaotic nature of MCI's can put tremendous stress on the health care system. In the aftermath of the 9/11 terrorist attacks, it became clear that a more comprehensive set of disaster management strategies and guidelines was required within North America (Frykberg 2003). While a comprehensive set of guidelines has yet to be developed, the rapid transfer of patients to the appropriate health care facility has been identified as a key component in the successful management of a mass casualty incident (Aylwin, König et al. 2006). This involves the management and coordination of pre-hospital stage treatment such as triage, transportation, hospital preparation and communication (Rehn, Andersen et al. 2010).

The challenges presented by mass casualty events are much different than those faced by the health care system on a daily basis. During a mass casualty, the number of critically injured patients is significantly larger and the injuries are typically quite varied and severe in nature (Frykberg 2004). From a management perspective, mass casualties require a shift from the more patient-focused style of treatment generally employed within the hospital to a more efficiency-based model in which the goal is to save as many people as possible with the limited resources available (Kennedy, Aghababian et al. 1996). This leads to the prioritization of patient care based on an assessment of the patients` chances of survival, with those who are deemed most likely to survive receiving treatment first (Jenkins, McCarthy et al. 2008). Pre-hospital trauma support guidelines indicate that, where possible, critically injured patients should be transported promptly to a level 1 trauma hospital (Einav, Feigenberg et al. 2004). This works well for an exclusive trauma system, in which there are only one or two major health care centers providing critically injured patient care. Within an inclusive trauma system, however, where all acute care hospitals participate in providing care for critically injured patients, patients will typically be sent to the nearest acute care hospital capable of caring for the patient (Physician 1993; Nathens, Maier et al. 2003; Utter, Maier et al. 2006).

This difference in practice between inclusive and exclusive systems is supported by an Israeli study that examined evacuation priorities in 33 Israeli mass casualties between 2000 and 2002 (Einav, Feigenberg et al. 2004). One of the most comprehensive studies of mass casualty evacuation priorities to date, this study examined the decision making process within Israel`s inclusive health care system and determined that within this system patients were typically evacuated to the nearest hospital rather than a level 1 trauma centre. The results of this study clearly demonstrated a relationship between the choice of evacuation hospital and the hospital's distance from the MCI. In this case, the likelihood of evacuation to a specialized trauma centre diminished as distance to the MCI increased. In addition, these findings were found to be applicable in both urban and rural areas of Israel (Einav, Feigenberg et al. 2004). The study concluded that the hospital nearest the scene of the incident typically received the largest number of patients. Critically injured patients were given minimal medical attention at the scene of the incident location and were then transferred to the nearest health facility for definitive trauma care.

Mass casualty pre-hospital care is comprised of three components: triage, treatment and transportation to the appropriate health facility (Rehn, Andersen et al. 2010). Triage is a critical factor in the effective management of mass casualty incidents and refers to the process of prioritizing medical care based on the medical condition of the patient (Kennedy, Aghababian et al. 1996; Moskop and Iserson 2007; Jenkins, McCarthy et al. 2008). Once triage has taken place, decisions regarding patient treatment and hospital transport will then be made. The smooth integration of all three components is critical in ensuring mass casualty patients are appropriately and efficiently treated.

Decisions regarding the evacuation of patients to hospital are related to both distance and capacity. Capacity is measured in terms of bed availability and is a critical element in a hospital`s ability to handle a surge, or sudden overwhelming influx of patients (Davis, Poste et al. 2005). While surges of this type can result in the deterioration of patient care, a hospital`s ability to care for critically injured patients is also correlated to the flow of patients into the hospital (Frykberg 2002; Hirshberg, Scott et al. 2005). For example, a level 1 trauma hospital may have the capacity to treat five critically injured patients, but if they all arrive within the first 30 minutes of the incident, the hospital`s ability to provide care may deteriorate. In order to control emergency room surge and effectively manage an MCI, hospital capacity and patient evacuation rates must be carefully monitored for each facility.

To date, most MCI research has focused on the management of hospital surge capacity, however, it may also be possible to prevent or delay surges by better directing the flow of patients during the initial stages of evacuation. Unfortunately, a means of providing information concerning patient flow to those at the scene of the incident has not yet been developed.

3.2.2 Overtriage and Patient Flow

Triage is an important factor in the management of patient flow and the first step in MCI pre-hospital care. Triage also guides the evacuation process, informing decisions regarding the health care facility to which the patient should be sent and the urgency of evacuation (Jenkins, McCarthy et al. 2008). A complex process at any time, triage is even more difficult in the midst of an MCI and some level of over or undertriage is to be expected (Plani 2009). Typically, overtriage is more common, with practitioners generally erring on the side of caution(Frykberg and Tepas 1988). While on a day-to-day basis this has very little effect on the health care system, this is not the case during a mass casualty. In such cases, an influx of overtriaged patients can cause critically injured patients to go without care unnecessarily. In fact, some evidence shows that overtriage during a mass casualty can be linked to loss of salvageable lives (Frykberg and Tepas 1988).

3.2.3 Controlling patient flow

Information regarding real-time hospital bed capacity is key to controlling the flow of patients from an MCI, in that it allows for evidence based decision-making regarding the evacuation of patients. In order to manage patient flow effectively, it is important to know not only where beds are available, but also when a patient was last sent from the incident to the hospital and when the patient is expected to arrive. This will enable the decision makers at the scene of the incident to better understand the situation at the hospital to which they are sending their patients. This information is particularly important early in the evacuation process where hospitals are not yet fully prepared for an influx of critically injured patients.

Information concerning overtriage is also helpful to those at the scene of the incident as this may impact bed capacity. If, for example, a patient is no longer classified as P1 or P2 (i.e critically injured) after secondary triage at the hospital, an ICU bed will no longer be required.

The following model aims to provide paramedics and others at the scene of an MCI with a tool to make evacuation decisions simpler and more effective.

3.2.4 Model

By providing real time information concerning hospital capacity, location and treatment specializations, the proposed model is intended to assist decision makers (paramedics, disaster management teams) at the scene of a mass casualty incident in more efficiently and appropriately evacuating patients. This web-based model requires no specialized software or hardware to operate and can be used on any laptop or desktop computer with internet access and a browser. The model is built to operate within the Lower Mainland region of British Columbia, Canada.

3.3 Methods

3.3.1 Data

Two sets of data were used in constructing this model: road network data and hospital location data. The road data is highly suitable for calculating travel time as it incorporates both speed limits and travel impedances (i.e. stop signs, traffic lights, etc.) which, in turn, allow for accurate travel time calculation. The data also provides the ability to control travel and impedance times. This is important, as travel times for an ambulance will differ from that of a regular vehicle. The fact that this data enables control of such variables heightens the accuracy of the results (Amram et all. 2011).

The second set of data utilized in this study is comprised of the locations of participating hospitals within the metro Vancouver region. In addition to geocoded hospital locations, the hospital dataset also contains attributes describing the hospital's capacity to receive mass casualty patients and the trauma level of each of the hospitals. The hospitals are represented as a set of GIS point features and are geocoded as close to the main emergency room access as possible (Amram et all. 2011).

In order to obtain results in a more immediate fashion, this model utilized pre-calculated driving times from each location on the road network to each hospital in the study area. The ODMatrix function within ESRI ArcGIS network analyst was used to make the driving time calculation.

3.4 Simulation Data

In order to test the model in a simulated, but realistic situation, mass casualty counts and injury descriptions from the 2005 London bombings were used. Data for this purpose was primarily obtained from a paper written by Aylwin et al. in 2006 which provided a detailed description of each of the four bombings in addition to background on how London`s largest hospital, the Royal London, handled the flow of critically injured patients. Further details are included in the following section.

3.4.1 Model Interface

The model interface has two principal windows for interaction with the user. The 'first or main' window allows the user to easily insert the location of the MCI on a digital map. The second or 'results' window displays the results of the analysis while the third or 'hospital info' window provides the user with the ability to view updated hospital information, such as capacity, and/or make decisions about which hospitals should be included in the analysis.

3.5 Using the model

The main window, which is visible upon initial start up, consists of two primary components: a map and a simple form to insert information regarding the MCI. The map is used to enter the MCI location. After this step is completed, the user will then use the form to provide a descriptive name for the MCI location and run the model. This initial step is illustrated in Figure 1.

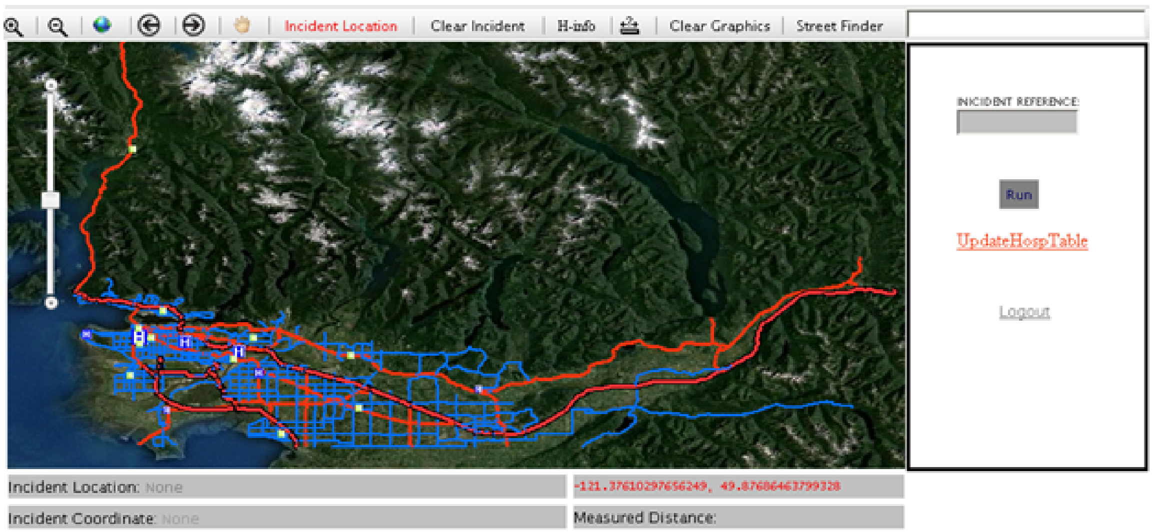

Figure 3-1 : The main window is the first window that the user sees when launching the model. It enables the user to insert the MCI location on the map and run the model.

The results window is visible upon running the analysis from the main window. The results window provides the user with information regarding estimated driving times to each hospital, up-to-date hospital capacity and utilization level, trauma level and also the last time a patient was evacuated to the hospital. Using a decision making algorithm, it also provides the user with a suggested hospital to which the next patient should be evacuated. The full extent of information provided is shown in Figure 2.

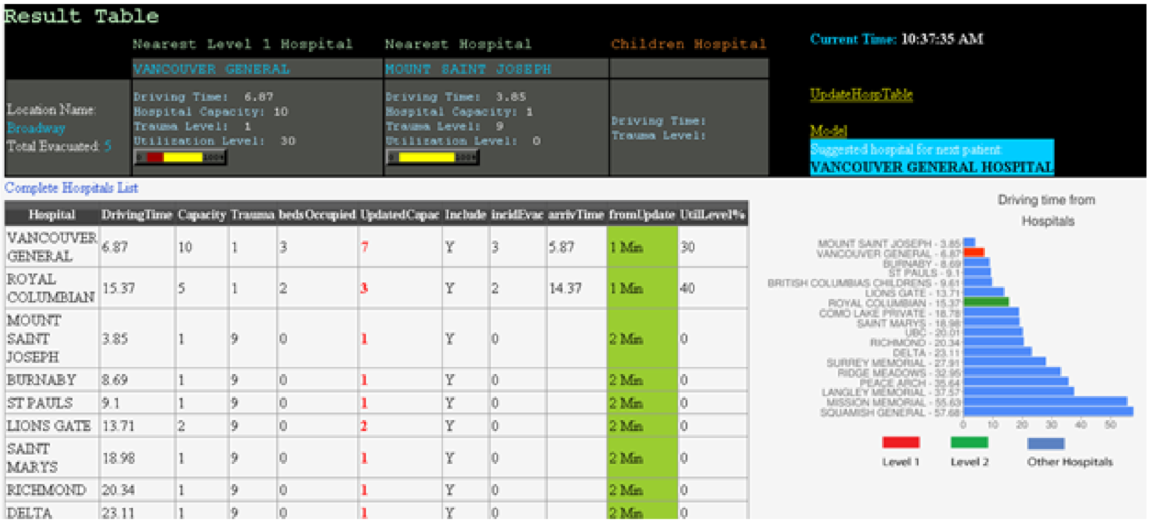

Figure 3-2: The results window is displayed immediately after the user runs the model from the main window. This window provides information regarding hospital driving times (from the MCI), and updated capacity. Hospitals with trauma level 9 depict non trauma hospitals.

The driving time estimation to each hospital is only an approximation. Although research comparing modeled driving times with actual driving times found that the driving time calculations produced estimations that were close to actual driving times, the driving time is only a calculation of the quickest way to drive from the incident location to any of the hospitals in the study area. The driving time does not take into account real life situations like road traffic (Gonzalez, Lerch et al. 2003). The value of the model's driving times lies in its ability to quickly provide an approximation of the incident location relative to that of the hospitals. When model driving times were compared with ambulance driving time data collected from two ambulance stations, quite a bit of variance was noted. This is primarily due to the unpredictable nature of traffic, differences in time of day, and differences between the route taken by the ambulance driver and the route calculated by the model.

The results window also provides real-time information regarding the bed capacity of each of the hospitals. Real time bed capacity is calculated by subtracting the number of evacuated patients from the total number of beds available at each hospital at the time the MCI (or MCI's, if more than one) occurred. In order for bed capacity to be accurately maintained, the user must record every patient transported to hospital within the model. Also provided in the results window is the time when hospital capacity was last updated by the user (i.e. the time at which the most recently evacuated patient was transported to the hospital). In addition, an estimate of the patient's hospital arrival time is also provided. The last item of information provided is the level of utilization at each of the hospitals. Utilization level is calculated by dividing the total number of patients evacuated (per hospital) by individual hospital capacity. The purpose in displaying this information is not only to provide an up-to-date snap shot of hospital capacity but also to help control patient flow to each hospital thereby helping to prevent surge. For example, if the utilization level within a specific hospital is high and the user is aware that a patient was only recently transported to the same hospital, the user can then assume that the hospital`s resources are being utilized at capacity and that the next patient may be better treated at a different hospital.

In order to assist the user in quickly coming to a decision, the results window also suggests a hospital to which the next critically injured patient should be evacuated. This is done using an algorithm that analyzes hospital capacity, utilization level, proximity and trauma level.

3.5.1 The `Hospital Info` window

The hospital info window provides a space for users to update the information that will be used in the analysis (e.g. number of patients evacuated or destination hospital), by enabling direct access to the table used to generate the information displayed in the results window (Figure 3). As the model is web based, this enables the information to be updated from different locations in real-time. This window also provides a space for hospitals to indicate that they cannot accept additional patients, informs users of the time of last update and enables hospitals to update bed capacity as it increases.

Figure 3-3: Shows the casualty evacuation update window. This window allows the user to update the hospital to which casualties were evacuated.

3.5.2 Sequence of Model Operations

Although the model was designed to become operational within seconds of an MCI occurring, up-to-date hospital capacity must be inserted before it can provide useful information. As a result, hospitals must update bed capacity in the hospital information window as soon as an MCI is declared. As updates are time marked for each particular hospital, users can easily see when the most recent updates occurred. Once the hospitals have updated their data, the users at the scene of the incident can begin running the model and adding their own updates as patients are evacuated. The model is designed to automatically refresh the hospital information table every 10 seconds (alternate intervals can be set by the user) in order to display up-to-date information in the results window.

3.5.3 Modelling Multiple MCI's

Modeling of multiple mass casualties can also be accomplished with this model, provided a separate model is used for each MCI. This is possible because for each MCI the model accesses the same centralized database containing real time hospital capacity and utilization level.

3.6 Testing the Model

3.6.1 The Model Parameters

The P1 and P2 casualty counts for those transported from Aldgate and King's Cross stations were used in testing the model. From Aldgate station, eleven P1 and P2 patients were evacuated within 64 minutes. From King's Cross station, ten patients were evacuated within a span of 108 minutes. As the exact evacuation time of each patient was not available, an evacuation frequency rate was calculated for each station and used instead. The evacuation frequency rate for patients from Aldgate station was calculated at one every 5.8 minutes. From King`s Cross, the rate was one every 10.8 minutes. The overtriage rate from each station was also used when testing the model. From Aldgate station, 3 of the 11 evacuees were determined to have been overtriaged upon arrival at the hospital, while from King's Cross, 4 of the 10 were overtriaged. Overtriage rates were incorporated within the testing in order to demonstrate the model's flexibility in updating real time bed capacity (Table1).

Table1. Counts of critically injured patients at each of the MCI's in the London Bombing (2).

	Aldgate	King's Cross	Edgware Road	Tavistock Square
Priority 1 or 2	11	10	17	17
Overtriage	3	4	15	13

Table 3-1: In the model simulation, the Aldgate casualty count was assigned to Waterfront sky train station in downtown Vancouver. Casualty counts from the King's Cross MCI were assigned to Broadway station.

These parameters were then applied to two similar locations within our study area. The chosen locations were Broadway and Waterfront sky train stations. Both of these stations are partly underground and both experience high commuter volumes, particularly during rush hours. In order to test our model, the Aldgate station casualty counts and patient flow frequencies were applied to the Waterfront sky train station. At the same time, the King's Cross patient counts and flow frequencies were applied to Broadway station. In order to simplify the modeling, both MCI simulations were set to start at the same time.

3.6.2 Generating Patient Flow

In order to generate patient flow from each of the MCI's in our simulation, a small utility was created. This utility generates patient flow based on parameters set by the user. The parameters are the incident evacuation duration and patient evacuation frequency. In addition, a model duration time input will let the user adjust the model time duration.

3.7 Results

This model has the capacity to rationalize decision making at MCI sites. By incorporating MCI location, hospital trauma level certification, and patient flow, it allows EMS to make decisions based on evidence. The results of the simulation show the hospital to which casualties should be evacuated in order to keep patient flow relatively even across all hospitals. There are two major trauma centres within the study area: Vancouver General Hospital (VGH) and Royal Columbian Hospital (RCH). From Waterfront Station, the driving time to VGH is approximately nine minutes, while RCH is around twenty minutes away. Broadway station is closer to both of these hospitals, with driving times of approximately seven minutes to VGH and fifteen minutes to RCH (Table 2).

Table2. Model driving time from each MCI to each of the major trauma hospitals.

	Vancouver General Hospital	Royal Columbian Hospital
WaterFront Station	9 Minutes	20 Minutes
Commercial Station	7 Minutes	16 Minutes

Table 3-2: Shows the model driving time from each of the MCI locations to the major hospitals in the study area.

Based on estimates of hospital size, bed capacity for the simulation was set at ten beds for VGH, five beds for RCH and one bed for each of the smaller hospitals. Figure 4 illustrates the patient evacuation frequency from each MCI location. As suggested by the model, the majority of the Waterfront station casualties were transported to VGH, while the Broadway station patients were sent to both VGH and RCH. After 35 minutes (plus transport time) RCH reached a utilization level of sixty percent. VGH reached the same utilization level soon after. VGH reached full capacity within 60 minutes and RCH at 65 minutes. Of the patients evacuated to hospital, four were found to have been overtriaged, requiring the model to make adjustments to utilization level, bed capacity and suggested evacuation hospital. Two of the four overtriaged patients were discovered prior to the two trauma hospitals reaching full capacity and two were discovered after full capacity had already been reached. Once full capacity was reached at these two trauma centres, the model began diverting patients to the hospital nearest the particular incident as illustrated in Figure 5.

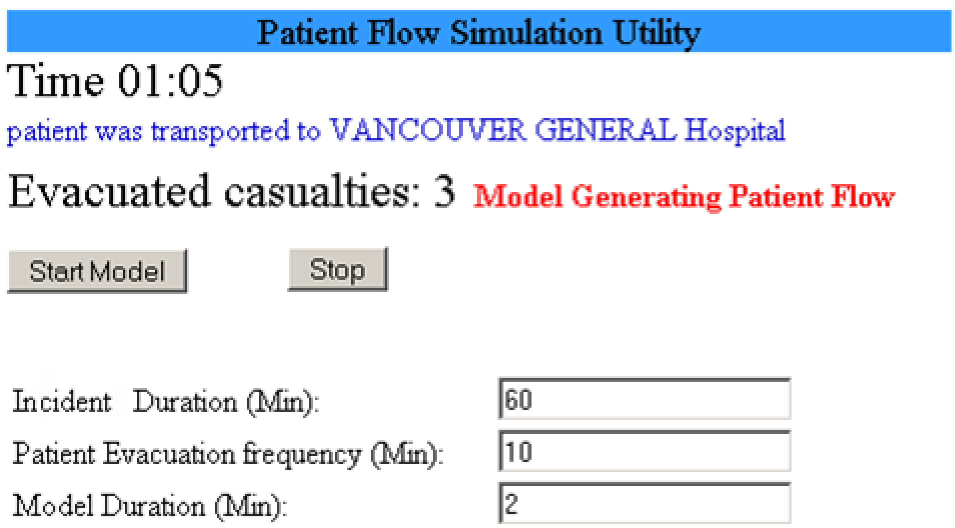

Figure 3-4: Shows the utility that generates patient flow. It allows the user to set the incident duration and time the frequency of patient evacuation. It also allows the user to speed up the simulation.

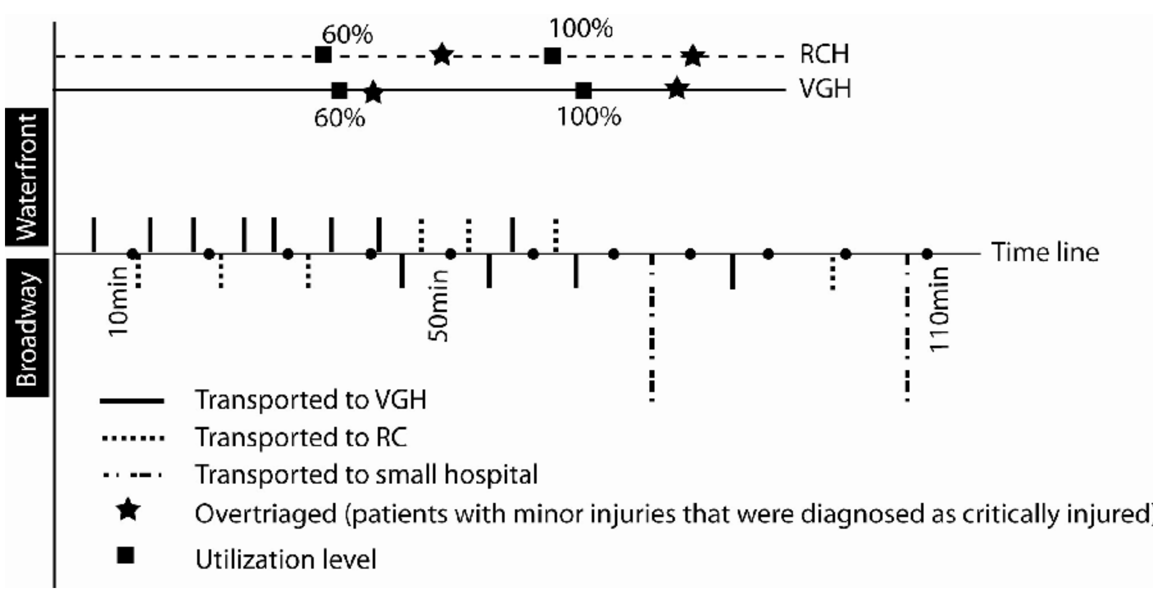

Figure 3-5: Displays the patient evacuation timeline from both MCI's. Patients are distributed to each of the trauma hospitals evenly in order to avoid an influx of patients at one specific hospital. The model also adjusts for any patients found to be overtriaged at the hospital.

3.8 Discussion

The dynamic and evolving nature of mass casualty incidents requires that decisions regarding pre-hospital management be made under extreme time pressure (Gonzalez and Brunstein 2009). Research into the real time dynamic decision-making (DDM) process indicates that most decision-making is based on past experience (Gilboa and Schmeidler 1995; Huang and Pan 2007; Gonzalez and Brunstein 2009). Therefore, the more experience one has in mass casualty management, the easier it is to make appropriate decisions under extreme conditions. However, given that the occurrence of mass casualty incidents is relatively rare. Only a few paramedics will face a large scale mass casualty during their career (Gonzalez and Brunstein 2009).

The proposed model is intended to reduce some of the uncertainty surrounding the evacuation of MCI patients. Although it builds upon several previously developed spatial models, only a few of these models were developed for use by EMS. Those models that were designed for EMS use focused on routing drivers to the incident location as opposed to routing between incident location and appropriate hospital, as is the case with this model (Huang and Pan 2007).

Problems with these earlier models include lengthy processing times, as a result of incorporating real-time traffic data, or lack of authenticity, due to the use of simulated traffic data (Derekenaris, Garofalakis et al. 2001; Huang and Pan 2007). By contrast, the model proposed within this paper provides estimated driving as one component in the decision making process. While the incorporation of real time driving information would further enhance this model, it would also significantly extend the time required for computer data processing (Derekenaris, Garofalakis et al. 2001; Ghiani, Guerriero et al. 2003). Although the model described in this study was able to avoid significant processing delays by utilizing pre-calculated driving times from each location on the road network to each hospital in the study area, the use of pre-calculated driving times also introduces some limitations. It does not, for example, allow for the input of travel impedances, like bridge closures, or construction, into the calculation or for the use of air transport.

3.9 Conclusion

The model described in this paper can be used in two different ways. First, it can be used to transfer real time information concerning casualty counts, hospital driving time and capacity so as to more easily and accurately manage patient evacuation from one or more MCI's. The second use of this model is in the simulation of evacuation from an MCI. In the simulation described in this paper, the model managed patient flow from the MCI so as to prevent one hospital from being overwhelmed by patients while other hospitals went unutilized. The effectiveness of this model is dependent upon the sharing of information between the hospital and the incident location. This can be challenging, especially in a mass casualty situation were the focus is on treating and transporting patients.

4: CHAPTER 4
CONCLUSION

The model presented in this thesis demonstrates the successful use of evidence based evacuation decision making during the pre-hospital stage of a mass casualty. The model's greatest contribution is its ability to provide users with information regarding the driving time to each hospital, the service level/specializations of each hospital and each hospital's real time capacity. This information is the first step in enabling first responders to make more informed decisions regarding the prioritization of patients to be evacuated. However, by using this information to suggest a destination hospital for each evacuee, the model also helps to manage patient flow. Accurate, up-to-date information is critical when determining how best to provide care for critically injured patients. At the same time, the effective management of patient flow during the pre-hospital stage not only improves the quality of care patients receive, but may also save lives.

Chapter 2 describes the development of the MCI model used in this study – and emphasizes its methodological construction. One of this model's core functionalities is the use of pre-calculated driving times. Pre-calculated driving times were utilized in order to provide results to the user as quickly as possible. The chapter also describes the integration between the web-based GIS functionalities that were developed using ArcGIS server api and the database management and visualization functionalities that were developed using ASP.NET.

Chapter 3 describes the testing of the model through the use of a simulation. Information from the 2005 London transit system bombings, in the form of casualty counts and patient evacuation rates, was used as input data for the model. Two simulated mass casualties were recreated within the model, imitating two of the four mass casualties that occurred in London. The results of the simulation demonstrated the model's ability to control the flow of patients to each hospital. By distributing the patients based on real-time knowledge regarding capacity, proximity of the hospital to the MCI and the hospital's capability to treat severally injured patients, the model was able to ensure that no one hospital was overwhelmed with patients. Several studies have highlighted the critical relationship between the rate at which casualties flow into a given hospital and that hospital's ability to provide quality care for patients (Frykberg 2002; Hirshberg, Scott et al. 2005). In this case, the model was able to improve control over casualty flow by providing real time information regarding hospital capacity. In addition, by opening two models simultaneously, each one corresponding to a different MCI location, over a web-based platform, the models were able to interact dynamically. As a result, the evacuation hospital suggested by each individual model, was able to take into account capacity changes caused by evacuations from the other MCI location (and updated in the second model) and/or by changes in triage status within the hospital (updated by staff within the hospital). Enabling hospitals access to the model is very important as during a mass casualty the rate of overtriaged patients is very high (Frykberg and Tepas 1988; Plani 2009). This stems from the fact that those performing secondary triage want to avoid undertriaging at any cost. Unfortunately, overtriaged patients can hinder a hospital's ability to provide adequate care to those whose injuries are truly critical (Frykberg and Tepas 1988). By enabling hospitals to update capacity, once the true extent of a patient's injuries are known (after secondary triage is performed within the hospital), the model allows for better evacuation decision-making. The implementation of this functionality is, however, completely dependent upon the provision of such information by the hospital.

4.1 Research Contribution

This thesis presents the first model for mass casualty evacuation prioritization. The model was envisioned as a means to seamlessly integrate all stages of the mass casualty evacuation process, from primary triage at the incident location through the transportation of patients to the hospital and the care that then takes place. The pre-hospital stage of mass casualty is difficult to manage due to its unpredictable, chaotic and dynamic nature. This model enables EMS practitioners at the scene of an MCI to make evidence-based decisions as to where patients are best evacuated.

Although research examining the effects of patient flow on patient outcomes has resulted in the development of several techniques that may assist hospitals in providing quality care in situations where patient flow rates are high, thus far, this research has taken place only at the hospital stage (Hick, Hanfling et al. 2004; Barbisch 2005; Barbisch and Koenig 2006; Kaji, Koenig et al. 2006). As yet, no models have been developed to control for patient flow at the pre-hospital stage. In an attempt to bridge this gap, the model proposed in this thesis is directed at controlling the rate of at which patients arrive at the hospital. By distributing patients relatively evenly between the qualified hospitals within the trauma system, the model allows better management of patient care within the hospital and maximizes the trauma system's ability to care for critically injured patients.

The model proposed in this thesis also suggests several technical ideas in order to enhance the model performance. For example, the use of pre-calculated driving times as a means to decrease processing time and to provide more immediate results creatively overcomes the difficulties with time lag found in real-time based driving calculations for multiple (i.e. hospital) destinations. In addition, the provision of real-time hospital capacity through the synchronization of multiple models around a centralized database allows for system-wide trauma services management. At the same time, the model also provides the location-specific information required to calculate driving time from the scene of a particular incident.

Finally, this model also provides a planning tool that can be used to help determine how to best locate emergency services when planning for large events. This can be done by running simulated evacuations based on the proposed location for the event.

In conclusion, the primary contribution of this thesis is the development of a web-based model that facilitates mass casualty triage decision-making. A secondary aim is to introduce to the research community, specifically those researchers interested in mass casualty and emergency services research, a model intended to assist health care providers at the pre-hospital stage of evacuation planning. Better decision-making at the pre-hospital stage can vastly improve patient outcomes.

4.2 Future Work

While in its current format, this model provides an innovative tool to assist in the prioritization of mass casualty evacuations, further developments would provide additional benefits. For example, by incorporating street closures and real-time traffic information into the driving time calculation, more realistic driving times could be provided. This could be done by improving data transfer over the server and by incorporating up-to-date driving conditions. Thus far, models utilizing real-time traffic data have proven insufficient for emergency services use. This is largely due to the complexity of obtaining traffic data in real time (Derekenaris, Garofalakis et al. 2001; Huang and Pan 2007).

The model could also be improved through the development of an interface that would enable it to operate on a mobile device (iPhone, etc.). This would allow much greater flexibility for those working at the scene of the incident. For example, it would provide EMS personnel on the way to an incident with a snap shot of real time bed capacity at each of the hospitals. It may, however, also limit certain functionalities and/or visualization capabilities.

Further improvements could be made by adding both a utility to determine the level of uncertainty within the model results and by creating a stand-alone version that could operate in the event of a power failure. At present, the model is dependent upon the existence of reliable communication links between models running at the incident location and the evacuation hospitals. As these links are essential in the determination of real time bed capacity, it would be beneficial to create a scaled down, stand-alone version that could be utilized during a communications failure. The use of a dedicated network server would also make communication between the models more reliable.

Adding a function to enable prioritizing of patient evacuation by air, would also improve the model as this would allow for comparison of air vs ambulance evacuation.

Finally, to more fully examine the model's utility it would be beneficial to test it during a large-scale emergency services exercise. Although the model's capacity was tested using a simulation, to truly understand its value, it should be tested in the field in a situation emulating a real life mass casualty. This would then allow health care practitioners to determine how feasible it would be to use this type of device in the midst of a crisis situation. Future research should also examine the usability of the model, the ease of interpreting its results and the quality of the visualization.

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