A STUDY OF AMBULANCE DISPATCHING POLICIES TO IMPROVE DISASTER RELIEF OPERATIONS: A CASE STUDY ON ISTANBUL

by

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This is to certify that I have examined this copy of a master's thesis by

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and have found that it is complete and satisfactory in all respects,
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ABSTRACT

In this study, different ambulance dispatching policies are tested by a simulation model for the post-disaster ambulance dispatching problem. After an expected earthquake in Istanbul, many people would be trapped under the collapsed buildings. While the rescue efforts continue, a massive number of patients would need to be transported from the affected areas to the hospitals by ambulances. Consequently, ambulances would be overwhelmed by the transportation requests. Our objective is to assess the performance of different ambulance dispatching policies, by simulating the ambulance dispatching operations in seven districts of Istanbul and their neighborhoods. There are two performance criteria. The first one is the overall average response time. Response time is divided into two. First one is the elapsed time from the rescue of the patient till the arrival of the patient to the emergency unit at a hospital (RTH), while the second one considers the time between rescue of the patient and leaving time of emergency department of the patient (RTT). The second criterion is the overall average service level. It is also divided into two based on reaching to hospital ($SL1$), and transferring the patient out of the emergency department ($SL2$). The rescue times of the patients, their first-treatment durations and travel times are represented as random variables. Real road data is used for setting the distances between neighborhoods and neighborhood isolation risks are also considered while establishing travel times. The tested ambulance dispatching policies are first-called-first-served (FCFS), shortest-distance-first (SDF), and most-critical-patients-first (MCPF). SDF dispatching policy works by assigning the ambulances to the nearest patients based on expected travel times. MCPF policy initially sorts people based on one of the three injury types, and assigns the ambulance to the nearest patient if there is a tie from the injury types. In the base case, we run the simulation

model assuming the availability of real-time information. The results show that SDF policy performs the best in terms of average service time but has problems with fairness. We analyze several what-if scenarios to investigate the effects of periodic information update, decreased travel times and inclusion of hospital emergency treatment times in separate cases. Our results indicate that intensive communication between ambulance drivers and hospital emergency coordinators is necessary to improve performance. Also, there is a need for additional ambulances to ensure effective transportation of victims to the hospitals and it is shown that average service times are highly sensitive to the balance between number of patients and number of ambulances. Moreover, opening temporary emergency hospitals in some neighborhoods would serve as a beneficial strategy increasing fairness among neighborhoods.

ÖZET

Bu çalışmada, felaket sonrası ambulans yönlendirme problemi için benzetim yolu ile farklı ambulans yönlendirme stratejileri test edilmiştir. Beklenen İstanbul depremi sonrası binlerce insanın yıkılan binaların altında kalacağı tahmin edilmektedir. Kurtarma çalışmaları devam ederken yaralıların büyük kısmının ambulanslar ile deprem bölgesinden hastanelere taşınması gerekeceği ön görülmektedir. Buna bağlı olarak çoğu yerde ambulans ihtiyacı çok yüksek seviyelere çıkacaktır. Bizim amacımız, İstanbul'un yedi ilçe ve onların mahallelerinde ambulans yönlendirme operasyonu benzetimi ile farklı ambulans yönlendirme stratejilerinin performansını değerlendirmektir. İki adet performans kıstası mevcuttur. Birincisi ortalama servis süresidir. Servis süresi iki tip olarak ele alınmıst ır. Birincisi, bir yaralının kurtarılışından ambulans ile birlikte hastanenin acil servis birimine varışına kadar geçen süre iken (RTH), ikincisi yaralının kurtarılışından hastane acil servisinden ayrılmasına kadar geçen süreyi kapsar (RTT). İkinci kıstas ise servis oranıdır. Bu kıstas da ikiye ayrılmıştır. Birincisi hastaneye ulaşma durumu ile ilgili iken ($SL1$), diğeri ise acil servisten ayrılma süresini baz almaktadır ($SL2$). Yaralıların kurtarılış süreleri, ilk yardım süreci ve yolculuk süresi rasgele değişkenler olarak ele alınmıştır. Mahalleler arasındaki mesafeyi görmek için gerçek yol bilgisi kullanılırken mahalle izole olma riskleri de yolculuk süresini belirlemek için göz önünde bulundurulmuştur. Test edilmiş ambulans yönlendirme stratejileri şu şekildedir: İlk-çağrıya-ilk-hizmet (FCFS), en-yakına-en-önce-hizmet (SDF) ve kritik-yaralıya-hizmet-önceliği (MCPF). SDF yönlendirme stratejisi ambulansı beklenen yol süresine göre en yakın yaralılara yönlendirme esası ile çalışır. MCPF stratejisi, triaj işlemi ile üç yara derecesinden en ağır yara derecesine sahip olan yaralıya en yakın ambulansı gönderir. Bu çalışmanın esasında benzetim modelini gerçek za-

manlı bilgi akışını varsayarak çalıştırmaktayız. Sonuçlar SDF stratejisinin ortalama servis süresi açısından en iyi yöntem olduğunu göstermekle beraber adaletli olma konusunda problemler gözlenmiştir. Periyodik bilgi güncellemelerinin, azalan yolculuk süresinin ve hastane acil yardım bakım sürelerinin sürece dahil edilişinin etkilerini araştırmak için ayrı ayrı vakalarda birçok "ya öyle olursa" senaryosu inceledik. Vardığımız sonuç, ambulans şoförleri ile hastane acil yardım koordinatörlerinin yoğun iletişimde olmalarının performansı artırmak için kaçınılmaz olduğunu göstermektedir. Aynı zamanda mağdurların hastanelere etkin ulaşımını sağlamak için ilave ambulanslara ihtiyaç duyulmaktadır ve ortalama servis süresinin de yaralı-ambulans sayısının dengesinden son derece etkilendiği ortaya çıkmıştır. Bunun dışında, mahalleler arasında adil hizmet dağılımını sağlamak adına yararlı bir strateji de bazı mahallelerde geçici acil yardım hastaneleri kurmak olacaktır.

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Chapter 1

INTRODUCTION

Istanbul, a metropolitan city with approximately thirteen million inhabitants, is under the impending threat of a catastrophic earthquake. In the aftermath of such an event, thousands of injured people would be seeking medical assistance. A massive number of patients need to be transported from casualty locations to hospitals by the ambulances. Patient transportation in daily emergency situations is a widely studied problem. Particularly, the initial deployment and dispatching of ambulances have been addressed extensively in the literature. In every day emergencies, since the number of injuries is not so high, patients are typically served in first-called-first-served order. However, in a mass casualty incident such as an earthquake, the sudden surge in demand that overwhelms the emergency response capacity complicates the problem.

A disaster is a perceived tragedy, being either a natural calamity or a man-made catastrophe. Disaster management activities can be considered in the four categories of mitigation, preparedness, response, and recovery [4]. In particular, emergency response is critical since the lives of many people depend on providing quick and effective services. Transportation of patients to medical facilities is a post-disaster response activity, for which pre-disaster preparedness increases its effectiveness. There are many uncertainties when preparing for a disaster. In the case of an earthquake, some of these uncertainties are: the Richter scale of the earthquake, the number of injuries occur in each neighborhood, road and traffic conditions, the outcome of the rescue efforts that generate the patient arrival stream, etc. In spite of the criticality of preparedness and planning, studies that incorporate the related uncertainties into the disaster response activities are few in number.

In this thesis, our objective is to assess the expected performance of the current medical emergency response system in response to a expected major earthquake in Istanbul. Specifically, our aim is to evaluate several ambulance dispatching strategies. In addition to assessing the 'sufficiency' of the current resources and response strategies, we are interested in evaluating various improvement options such as increasing the number of available ambulance units and establishing temporary emergency units to respond to the needs of the earthquake victims.

We use two performance criteria in evaluating system performance. The first one is related to overall effectiveness of the response system and is measured by the average rescue to hospital time and average rescue to transfer time (transfer out of the emergency department in the hospital). Rescue-to-hospital-time (RTH) spans the time from the time that the patient was rescued until the arrival of the patient to a hospital with an ambulance while Rescue-to-transfer-time (RTT). The second criterion is service level. It is the measurement of percentage of patients served in five days. Service level performance criterion is divided into two categories which are $SL1$ and $SL2$ based on patient's reaching to hospital time and transfer out of the emergenceny department respectively.

We simulate the transportation of patients after an expected earthquake in seven districts of Istanbul that have higher earthquake damage risk. The studied districts are Bahçelievler, Güngören, Zeytinburnu, Bağcılar, Esenler, Bayrampaşa and Bakırköy. These districts have a total of 99 neighborhoods. These areas form an almost-convex region and are also highly vulnerable to the expected earthquake. We have assumed a closed system, which means that the resources of the studied seven districts can not be used by outer areas and the demand of the studied areas can only be served by the supply in this area.

Due to the high number of injuries, the ambulance service system is expected to be overwhelmed after the disaster. The services would be impeded by adverse road and traffic conditions. It is likely that some roads will suffer traffic congestion. Further, some roads may be partially or totally damaged, or may be blocked by collapsed buildings. Dispatching policies other than FCFS may be necessary in this extra-ordinary environment. We aim to capture the post-disaster conditions realistically by using previous earthquake risk analysis and actual road data, and incorporate them into the policies. Therefore, we have offered two alternative policies which are shortest-distance-first (SDF) and most-critical-patient-first (MCPF). In SDF policy, an ambulance is assigned to the patient whose location is nearest based on the expected travel times to the ambulance location. In MCPF policy, ambulances are assigned to the patients based on the severity of patients' injuries and more critically injured patients are served first.

The data set of the simulation model for the seven districts is based on the JICA report [3], master thesis of Sezer Gül [1] and ArcGIS Istanbul road map [2]. The JICA report is prepared by the Japanese International Cooperation Agency for Istanbul Metropolitan Municipality. In this report, most likely earthquake scenarios have been identified and damage estimates are given. We use the 'ratio of heavily damaged buildings for each neighborhood' from the JICA report to estimate the number of injuries of neighborhoods; and the 'isolation probabilities for each neighborhood' from the JICA report to estimate the average travel time between neighborhoods. The time interval that is studied in this simulation spans the five days after the disaster strikes.

The remainder of this thesis is organized as follows. In Chapter 2, a brief description of the previous studies that are related to emergency medical transportation, disaster patient transportation, dispatching and deployment decisions and emergency vehicle simulation are given. In Chapter 3, the data set preparation, model assumptions and methodology are presented. In Chapter 4, the results are presented. We test different dispatching policies under varying parameters and realistic conditions, and system improvement options are tested by adding temporary emergency hospitals and new ambulances to the emergency service system. In the end, Chapter 5 gives a summary with concluding remarks.

Chapter 2

LITERATURE REVIEW

Some accidents or unexpected events occur and someone may get injured or many people demand periodic controls and both of which require an ambulance in order to get to the hospital. In that case, the deployment of ambulances and dispatching of them is not a trivial problem because in general, ambulances are not overwhelmed by the requests. Therefore, FCFS policy is implemented in daily life by assigning the closest idle ambulance to the earliest request. However, in the case of a post-disaster situation, dispatching problem becomes very complicated. In catastrophic disasters, ambulances are not enough to answer all the requests by FCFS manner due to heavy load of patients. Consequently, there are many studies about daily life emergency dispatching problem while there are limited number of studies for post-disaster cases. One of the latest medical review papers is written by Brandeau et al. [5]. In their review, the authors examined a large section of best practice guidelines for diverse models used in health sector responses to disasters. They have categorized the related literature based on disaster, modeling methodology, geographical setting, and purpose of study. This review paper is useful to understand the different approaches in disaster management. The authors concluded that the models should address real-time situations, be designed for maximum usability, and must have good model reporting. In our study, we try to use this review's fundamental conclusions.

2.1 Emergency management strategies for non-disaster cases

In the literature, there are many studies on everyday emergency medical services. One of the related papers to our work Haghani et al.[6]. In their paper, the authors concentrate on developing an optimization model for flexible dispatching strategies that take advantage of real-time traffic information. They formulated their problem as an integer programming problem, and a simulation experiment is conducted in order to provide a conceptual design of a real-time EMS system. In the simulation, alternative assignment strategies were analyzed to test the performance of this model under various circumstances, namely, different accident occurrence rates, route change strategies and dynamic travel times. Two of their studied ambulance dispatching policies are the same with our dispatching policies which are FCFS and nearest origin assignment policy. The name of the second policy is SDF policy in our study. Their model does not include post-disaster situation but includes useful insights on emergency vehicle dispatching. In our case, no real-time traffic information is present so direct application of their model to our problem is not feasible.

Andersson and Varbrand [7] is one of the latest papers on emergency response. The authors describe the development of decision support tools for automatic ambulance dispatching and dynamic ambulance relocation. They explain the ambulance dispatching problem as choosing which ambulance to send to a patient. The authors develop an algorithm based on priorities of the calls, and try to establish a decision support tool based on this algorithm in order to minimize waiting times of the patients. The first part of this work is directly related to our paper but their algorithm is not suitable to implement in large scale incidents. Their second contribution is the dynamic ambulance relocation problem, which occurs in the operational control of ambulances. The authors try to evaluate the set of ambulance station locations. Their claim is that, not all ambulance calls are urgent, and non-urgent transportations can be ordered several days in advance, making it possible to perform some sort of transportation planning. They perform computational tests using a simulation model to show that the tools are beneficial in reducing the waiting periods for the patients.

Maxwell et al.[8] claim that the increasing availability of geographic information systems and the increasing affordability of computing power have created ideal conditions for bringing real-time ambulance redeployment approaches to productive implementation. Therefore, they present an approximate dynamic programming approach for making real-time ambulance redeployment decisions in an emergency medical service system. Their main decision is where idle ambulances should be redeployed so as to maximize the number of calls reached within a delay threshold. They formulate a dynamic program that involves a high-dimensional and uncountable state space, and the difficulty arising from those factors are overcome by approximations to the value function that are parameterized by a small number of parameters.

2.2 Emergency management strategies for disaster cases

The studies mentioned above are not related to the disaster cases. For a disaster situation, there has been quite a number of studies on casualty transportation by medical emergency services. The previous work of this thesis is also related to post-disaster disaster patient transportation problem and is performed by the thesis of Sezer Gül [1]. In Gül's thesis, dynamic integer programming model is performed for the post-disaster patient transportation problem is performed, and the results present the locations and the capacities of post disaster temporary emergency hospitals which are going to be opened after the expected earthquake in Istanbul. Besides, decision of patients' transportation to hospitals is performed dynamically. The capacities of emergency units and the locations of ambulances are updated continuously.

In their paper, Haghani and Oh [9] have addressed the issue of a multi-commodity, multi-modal network problem with time windows for post-disaster operations. Basically, the authors deal with determining the detailed routing and scheduling of the available transportation modes, delivery schedules of the various commodities at their destinations, and the load plans for each of the transportation modes. They have developed two heuristic algorithms, one of which deals with utilizing an inherent network structure of the problem with a set of side constraints and the other solves the problem with an interactive fix-and-run heuristic. Fiedrich et al. [10] consider the overall logistics problem after a disaster. Their main goal is to minimize the total number of fatalities. The authors offer a dynamic optimization model called ALLOCATE for this problem. This model classifies the operational areas as SAR (search and rescue), stabilizing and immediate rehabilitation. Moreover, they also classify depots, hospitals and crossroads. Their model is influenced by several factors like survival rate for trapped victims, probability of secondary disasters, survival rate of rescued persons without medical treatment, transportation time and time to complete the work. The authors do not offer an exact method, but propose different heuristics to solve the model, and they claim that simulated annealing is the best.

Barbarosoglu and Arda [11] also developed a multi-commodity, multi-modal network flow formulation to describe the flow of material over an urban transportation network. Essentially, their paper proposes a two-stage stochastic programming model to plan the transportation of vital first-aid commodities to disaster-affected areas during emergency response. The authors address the problem of planning the transportation of vital first-aid commodities and emergency personnel to the disaster-affected areas by developing a generic modeling framework. Due to the uncertainty character of a post-earthquake situation, they treated this problem as a stochastic problem where randomness arises not only from demand but also from supply and route capacity perspectives as well.

Yi and Kumar [12] used a heuristic model to solve the post-disaster transportation problem with Ant Colony Optimization Algorithm. The authors combined the transportation of patients and supplies. Depending on the service rates, some hospitals have long queues.

Gong et al. [13] describe the concept of 'data fusion' as the science of efficiently organizing and interpreting massive amounts of data. The authors use this concept as a core to develop a dispatching and routing method for emergency vehicles in a disaster environment. In their model, they consider the patient priority, cluster information and distance as the influencing factors. The information of casualties and the road status is reported by sensors while the information on each patient is composed of his/her location and injury class. Casualties are classified into three priority categories of severe, moderate and mild injuries. Information on each link (road) is composed of its level of damage and the probability associated with it. In addition, the authors also consider the waiting time at the hospital. Gong and Batta [14] consider ambulance allocation and reallocation models for a post-disaster relief operation. The authors use a deterministic model for a disaster strike to allocate the ambulances to each cluster initially. The problem differs from Gong's PhD thesis [15] by adjusting a set of ambulances serve only one cluster until the cluster no longer exists which means that the ambulances must serve all the patients in that cluster till the end. The authors also study the problem of reallocating ambulances between clusters as the disaster evolves.

2.3 Triage

Triage is the process of prioritizing patients based on the severity of their condition. This rations patient treatment efficiently when resources are insufficient for all to be treated immediately. Jenkins et al. [16] indicate that mass-casualty triage is developed as a wartime necessity at first and later, it has become a civilian tool. They indicate that, several triage tools have been developed, however evidence to support the use of one triage algorithm over another is limited. The reason is that no studies evaluated existing mass-casualty triage algorithms regarding ease of use, reliability, and validity when biological, chemical, or radiological agents are introduced. The purpose of their paper is to explain the development of mass-casualty triage and those algorithms that have been developed for civilian populations. Moreover, they review those algorithms based on reliability and validity and discuss the need for empirically derived and validated algorithms. This paper is relevant to our work because one of our dispatching policies (MCPF) depends on field triage so that ambulances could be assigned for the more critically injured patients.

2.4 Other related topics

Although coverage problems are not directly related to emergency vehicle dispatching problems, some papers are useful to get some insight. One of them is written by Batta and Mannur [17] who propose a criterion for coverage that is suitable for two kinds of applications: (i) location of fire trucks in a geographical area in which some demands require multiple fire trucks, and (ii) location of ambulances in an environment in which large demand leads to unavailability of the most desired response unit. The authors claim that their models were explicitly designed to address different coverage requirements for demands, depending on how many units are required to respond to a demand. Consequently, they classify priority issues for the critical demands that have stricter coverage requirements.

Several review papers exist in the emergency management literature. One of these is written by Simpson and Hancock [18]. In their paper, they review the operational research foundation in emergency response, and they highlight that most of the studies are based on well-structured problems of emergency services. However, on the other side, most of the emergency response area is not well-structured. Therefore, emergency response requires the management of disorganization while operations research traditionally focused on the management of organization. The authors note that the emergency response could be a growth area for the next fifty years.

Queueing models are important tools in determining patient waiting time in the disaster area. One of the oldest papers for modeling emergency dispatching queuing models is written by Larson [19], who proposed the hypercube queuing model that has since become an important tool for planning emergency service systems. This model is related to our model since it considers urban environments in which servers travel to serve clients. In [19] exact solution for the queuing model for multiple (at most 15) servers. Some of the performance measures are mean response times, workloads of each servers, and fraction of dispatches of each server to each region. Following on this initial work, Larson [20] proposed an approximate hypercube model. This paper offers an approximate procedure for computing some performance measures for urban emergency service systems. This model is also applicable for more than fifteen servers and it is very useful for ambulance deployment and redeployment problems.

2.5 Contributions of this study

Our study is a continuous-time simulation of post-disaster patient transportation by ambulances in seven districts of Istanbul. Our objective is to assess the performance of different ambulance dispatching policies, by simulating the ambulance dispatching operations in seven districts of Istanbul and their neighborhoods. Specifically, our aim is to evaluate several ambulance dispatching strategies. We have observed that it is essential to teach triage to rescue teams and military units, also intensive communication between ambulance dispatchers or drivers and hospital coordinators is necessary. In addition to assessing the 'sufficiency' of the current resources and response strategies, we are interested in evaluating various improvement options such as increasing the number of available ambulance units and establishing temporary emergency units to respond to the needs of the earthquake victims.

Chapter 3

ASSUMPTIONS, DATA GENERATION AND METHODOLOGY

The post-disaster ambulance dispatching problem is subject to a setting with many stochastic elements. Moreover, the problem is inherently large scale and requires the consideration of a high number of states and actions dynamically. Hence it is very difficult to find optimal dispatching policies using analytical methods. For this reason, we utilize simulation as a powerful tool to imitate the real environment and understand the interactions among stochastic elements in this large-scale problem under several dispatching policies.

3.1 Notations, definitions, performance criteria

We use the following notation and definitions to evaluate system performance.

R=Number of replications (set to 10 in our experiments).

N=Number of neighborhoods (It is 99 for the 7 districts of Istanbul).

K=Number of injury types (There are 3 injury types).

$N(j, r)$=Denotes the number of patients originating from neighborhood j in replication r, where $j \in \{1, 2, \ldots, N\}$, $r \in \{1, 2, \ldots, R\}$.

$P(r)$=$\sum_{j=1}^{N} N(j, r)$, where $j \in \{1, 2, \ldots, N\}$, $r \in \{1, 2, \ldots, R\}$.

$RTH(i, r)$=Denotes the rescue-to-hospital time, that is the length of the time interval starting from the time when patient i is rescued until the arrival of patient i to a hospital with an ambulance in replication r, where $i \in \{1, 2, \ldots, P(r)\}$, $r \in \{1, 2, \ldots, R\}$.

$RTH(i, j, k, r)$=Denotes the rescue-to-hospital time, that is the length of the time interval starting from the time when patient i with injury type k in neighborhood j is rescued until the arrival of patient i to a hospital with an ambulance in replication r, where $i \in \{1, 2, \ldots, P(r)\}$, $j \in \{1, 2, \ldots, N\}$, $k \in \{1, 2, \ldots, K\}$, $r \in \{1, 2, \ldots, R\}$.

$\overline{RTH}(r)$=Average RTH in replication r, where $r \in \{1, 2, \ldots, R\}$.

That is $(\sum_{i=1}^{P(r)} RTH(i,r)/P(r))$

$\overline{RTH}$=Average RTH over all replications. That is $(\sum_{r=1}^{R} \overline{RTH}(r)/R)$

$\overline{RTH}(j,r)$=Average RTH of neighborhood j in replication r, where $j \in \{1, 2, \ldots, N\}$, $r \in \{1, 2, \ldots, R\}$. That is $(\sum_{i=1}^{N(j,r)} RTH(i,r)/N(j,r))$

$\overline{RTH}(j)$=Average RTH of neighborhood j over all replications, where $j \in \{1, 2, \ldots, N\}$. That is $(\sum_{r=1}^{R} \overline{RTH}(j,r)/R)$

We further define the following to account for the service time in the hospital in addition to RTT.

$RTT(i,r)$=Denotes the time interval starting from the time when patient i is rescued until the departure of patient i from an emergency service in a hospital, where $i \in \{1, 2, \ldots, P(r)\}$., $r \in \{1, 2, \ldots, R\}$.

$RTT(i,j,k,r)$=Denotes the time interval starting from the time when patient i is rescued until the departure of patient i, who has an injury type k and originated from neighborhood j, from an emergency service in a hospital in replication r, where $i \in \{1, 2, \ldots, P(r)\}$., $j \in \{1, 2, \ldots, N\}$., $k \in \{1, 2, \ldots, K\}$., $r \in \{1, 2, \ldots, R\}$.

$\overline{RTT}(r)$=Average RTT in replication r, where $r \in \{1, 2, \ldots, R\}$.

That is $(\sum_{i=1}^{P(r)} RTT(i,r)/P(r))$

$\overline{RTT}$=Average RTT over all replications. That is $(\sum_{r=1}^{R} \overline{RTT}(r)/R)$

$\overline{RTT}(j,r)$=Average RTT of neighborhood j in replication r, where $j \in \{1, 2, \ldots, N\}$., $r \in \{1, 2, \ldots, R\}$.. That is $(\sum_{i=1}^{N(j,r)} RTT(i,r)/N(j,r))$

$\overline{RTT}(j)$=Average RTT of neighborhood j over all replications, where $j \in \{1, 2, \ldots, N\}$. That is $(\sum_{r=1}^{R} \overline{RTT}(j,r)/R)$

The first performance criterion while comparing the dispatching policies is $\overline{RTH}$. In the case of adding emergency service times in hospitals to the simulation, $\overline{RTT}$ becomes the first performance criterion.

The second performance criterion is service level (SL). It is the measurement of percentage of patients served in five days. Service level performance criterion is divided into two categories which are $SL1$ and $SL2$ based on patient's reaching to hospital time and transfer out of the emergenceny department respectively. The service level is taken based on total simulation time, which is five days. Also service levels based on one to ten hours are also estimated. Below are the general notations for service levels, but all those notations are actually represented as $SL1$ or $SL2$ instead of SL only.

$SL(r)$=Denotes the service level of all patients in replication r, where $r \in \{1, 2, \ldots, R\}$.

$\overline{SL}$=Average service level of all patients for all replications.

$SL(k, r)$=Denotes the service level of patients with injury type k, where $k \in \{1, 2, \ldots, K\}$., $r \in \{1, 2, \ldots, R\}$.

$\overline{SL}(k)$=Average service level of all patients with injury type k for all replications, where $k \in \{1, 2, \ldots, K\}$..

$SL(j, r)$=Denotes the service level of patients in neighborhood j in replication r, where $j \in \{1, 2, \ldots, N\}$., $r \in \{1, 2, \ldots, R\}$.

$\overline{SL}(j)$=Average service level of all patients in neighborhood j for all replications, where $j \in \{1, 2, \ldots, N\}$..

$SL(j, k, r)$=Denotes the service level of patients in neighborhood j with injury type k in replication r, where $j \in \{1, 2, \ldots, N\}$., $k \in \{1, 2, \ldots, K\}$., $r \in \{1, 2, \ldots, R\}$.

$\overline{SL}(j, k)$=Average service level of all patients in neighborhood j with injury type k, where $j \in \{1, 2, \ldots, N\}$., $k \in \{1, 2, \ldots, K\}$.

3.2 The centralized emergency dispatching system

In a post-disaster situation, it is crucial to have a centralized system that controls all dispatching decisions of ambulances. Lack of a centralized system will create disorganization and reduce efficiency while dispatching ambulances; therefore it will increase waiting times of the victims and reduce their chances for survival. In the simulation, we have assumed that a centralized emergency dispatching system exists, and hence, all calls requesting ambulances must be made to the central response unit. In Istanbul case, this central response unit is Disaster Coordination Center (AKOM).

3.3 Continuous-time simulation and total time of the simulation

The simulation model is implemented as a continuous-time simulation. Time increments of one minute is considered. There are two reasons for choosing continuous-time simulation instead of discrete-event simulation. The first one is that there are thousands of ambulance request calls and ambulance decisions to carry the patients to the hospitals that need to be simulated. In a moderate instance of this simulation, the number of these discrete events becomes almost 100,000. The second reason is that, a minute is quite a small and adequate amount of time to make quick decisions after a disaster. The total run time of the simulation is five days. The reason is that; it is nearly impossible for a patient to survive more than five days after the disaster. In this simulation, it is assumed that the patient rescue process stops after 88 hours. Although the arrival of a new patient stops, some patients may not be carried to a hospital immediately by an ambulance due to the fact that the number of patients overwhelms the number of ambulances.

3.4 The patient arrival process and the estimated number of patients throughout the neighborhoods

In the rescue efforts, people are rescued one by one, or in batches of several people. We assume that rescuers request ambulance(s) by calling the central response unit (AKOM). AKOM must decide which ambulance to send to which patient.

The number of patients that may occur from all 99 neighborhoods depends on the population as well as the amount of destruction in these neighborhoods. The populations are based on the 2009 population data of ESRI Company. The exact percentage of destruction can not be known in advance of the earthquake, but Japanese International Cooperation Agency (JICA) prepared a report for the expected percentage of destruction in each neighborhood [3]. In our study, JICA report is the primary source for estimating the expected number of patients for each neighborhood. The expected number of patients requesting ambulances for each neighborhood is assumed as the size of the population of the neighborhood times one fifth of the upper limit of expected ratio of heavily damaged buildings. The reason of using one fifth of the upper limit is due to the JICA report [3]. In JICA report, expected casualty numbers of districts are given but expected number of casualties for neighborhoods data is not present. Therefore, we need to adjust the total number of expected casualties for each district to the expected casualty number of JICA report while generating data. It is observed that one fifth of the upper limits of expected ratio of the heavily damaged buildings times the population of neighborhood is a 95 percent fit. The results of this estimation is listed in Table 4.

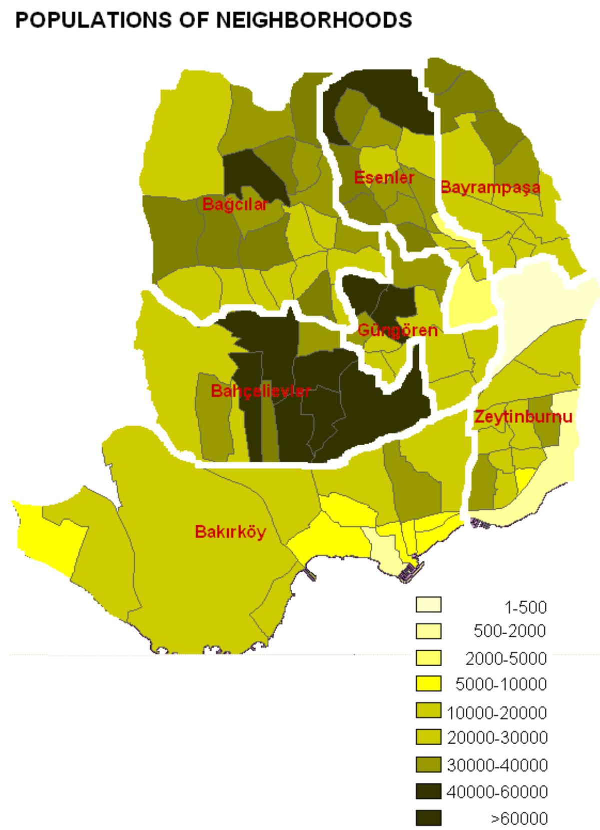

Figure 3.1: Populations of the seven studied districts taken from [2]

The arrival of a patient means that an ambulance request is made by a call to AKOM.

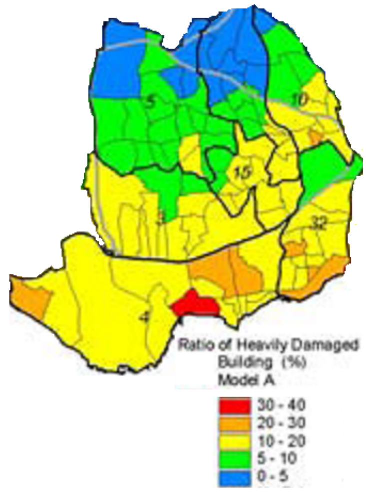

Figure 3.2: Ratio of heavily damaged building [3]

There might be batch arrivals because more than one ambulance might be requested in the same call. We assume that the call arrivals can be modeled as a Poisson process, and hence, the interarrival times are exponentially distributed. The rates of the exponential distributions vary for different neighborhoods, due to the different population sizes, different expected ratios of heavily damaged buildings. The rates of the exponential distributions that govern the arrivals of ambulance requests for each neighborhood become inputs to the simulation. It is assumed that, all patients are located in their neighborhoods' centers.

3.5 The number, location and capacities of ambulances and hospitals

The ambulance and hospital numbers and their locations are taken from a previous study of Gül [1]. In this study, the author listed all of the emergency medical units of the city, but we used the data on seven studied districts in this work. There are a total of eighteen hospital locations in the studied seven districts. These hospital locations are based on grouping of some medical facilities. In their study, they group some of the close medical facilities and hospitals and report as one hospital. Initially, ambulances are assumed to be in the hospitals. The capacity of an ambulance is assumed to be one. The capacities of hospital emergency service units are also from Gül [1]. For the locations of hospitals and ambulances, center of neighborhood assumption is used. Therefore, the distance between an ambulance and a patient refers to the distance between the neighborhood of the ambulance and the neighborhood of the patient. The data set for medical units is listed in Table 5 and the locations are given in Figure 1.

3.6 The travel times between hospitals and neighborhoods

In this work, we have used a geographical software, ArcGIS, developed by ESRI. In this software, the distances between each neighborhood and each hospital are calculated. The distances do not directly determine the travel times between neighborhoods and hospitals. The travel times depend on the average velocity on the roads. In the simulation model, two different average velocities are tested, which are 25 km/h and 35 km/h. However, these values are not final; they are actually decreased by the isolation risk probabilities that are estimated in the JICA report for each neighborhood 2. Coefficients are used to increase travel times. We have given coefficients to each neighborhood between 1 and 2 based on isolation risk map of JICA report 2. For example, if a neighborhood's 30 percent of its total land has high risk of isolation, then the neighborhood's coefficient is 1.3. If 60 percent of the lands of the neighborhood has high risk of isolation, its coefficient is 1.6, and if all of the neighborhood area has high risk of isolation, its coefficient is 2. Coefficients and initial travel times between neighborhoods and hospitals are listed in Table 2. The results in this Table must be multiplied by 6/25 for 25 km/h because the listed values are based on 6 km/h velocity. Depending on these coefficients, the average velocity of the ambulances can be decreased by 10 percent to 75 percent, so the travel times can be increased up to 400 percent of the travel times found only from distances. A step-by-step example for finding the travel time is as follows:

1) Calculate the distance between a neighborhood and a hospital (e.g., assume that the result is 4.2 km).

2) If the velocity is set to 25 km/h, then ideally, an ambulance must reach to the destination in 0.17 h, which is equal to 10.08 min.

3) However, this is not the case because of the isolation risk probabilities. The road blockages can either occur by ruins of buildings or traffic jam. From the JICA report, look at the coefficient of that neighborhood in Tables 2 and 3 (assume that it is 1.6). Also look at the coefficient of the ambulance's neighborhood (assume that it is 1.2). The ambulance must travel in both of the neighborhoods, therefore multiply both 1.6 ve 1.2 and take 1.92 as final coefficient.

4) For the final travel time, multiply 10.08 min and 1.92 in order to get the expected travel time, which is equal to 19.35 min.

5) This final value is now input to the simulation as a mean travel time between the specified neighborhood and hospital.

Travel times are normally distributed with means found by the described process above. Mean travel times between all neighborhoods and hospitals are listed Tables 2 and 3. There are two basic assumptions in this process. The first one is about step 3. In general, there are other neighborhoods on the road direction between a hospital and a neighborhood. But, the isolation risk probabilities of these intermediate neighborhoods are not taken into consideration. The second assumption is that, if the normal distribution gives a travel time less than 5 min, it is considered as a 5 min or if it gives a travel time more than 450 min, than it is considered as 450 min.

3.7 Injury types

Triage could save many lives after a mass casualty incident. Jenkins et al. [16] indicate that mass-casualty triage is developed as a wartime necessity at first and later it has become a civilian tool. After the disaster, it is assumed that rescuers could classify the patients into at least three categories. Therefore, our simulation model considers three injury types of type 1, type 2 and type 3. While considering some of the policies in the simulation, it is assumed that rescuers who save people and call ambulances are capable of categorizing the patients into these three types of injuries. Type 1 represents severe injuries, type 3 represents minor injuries and type 2 injuries are in the middle. In the simulation, an ambulance is dispatched if an ambulance is requested for a patient. Generally, people do not request an ambulance when there is a minor injury, however a vehicle is mandatory for major injuries. Therefore, an ambulance is more likely to carry a patient with more severe injury. The arrival probabilities of injury types that request ambulances are as follows: a) Type 1 injury: 0.6, b) Type 2 injury: 0.3, c) Type 3 injury: 0.1. It is assumed that the listed emergency service capacities of the hospitals are committed to the injuries that are carried by the ambulances. This means that the patients that are carried by other vehicles or patients that walk to the emergency services do not decrease the available capacity of the listed emergency service capacities.

3.8 Ambulance minimum reassignment time in the hospital

Ambulances are kept busy as long as there are patients waiting for an ambulance. In such a case, when an ambulance arrives to a hospital with a patient, it is immediately reassigned to a new patient and is dispatched in the next minute. This means the time interval between unloading the patient and reassignment of this ambulances is one minute. This process could take a few minutes but since it is difficult to estimate this duration exactly, we made this assumption.

3.9 Non-disaster related ambulance requests

On a regular day, some ambulances are requested and many stay idle. The closest ambulance can be easily assigned to a request. However, after a disaster, ambulance call volume increases dramatically. As a result, the regular ambulance requests take a small portion of the ambulance request calls. Hence, they are ignored in the simulation.

3.10 Ambulance dispatching policies and return policies

Three dispatching policies are considered. These are: First-called-first-served (FCFS), shortest-distance-first (SDF), and most-critical-patient-first (MCPF).

FCFS policy assigns idle ambulances to patients based on the arrival times of the patients. The patient who requests an ambulance first is served first. Therefore, patients are served in chronological order. Note that there could be a tie between patients in time chronology when there is a batch arrival, but this creates a very negligible difference between patients in the batch, may be a couple of minutes.

SDF policy assigns idle ambulances to patients who are in nearest neighborhoods based on expected travel times. Therefore, patients who are closest to ambulances with this expected travel times are served first. If there is a tie in distances, then patients are served with FCFS policy. Note that, instead of distances, we use expected travel times, which are adjusted with respect to isolation risk probabilities in the neighborhoods.

The third policy is MCPF. This policy assigns ambulances to patients based on the severity of injury of the patients. There are three types of injuries in the simulation model. Consequently, severe (type 1) injuries are served first. Then moderate (type 2) injuries has priority over type 3 injuries. If there is a tie in the injury type of the patients, SDF policy is applied. If there is a tie again, then FCFS policy is applied to these patients.

When an ambulance picks up a patient, this ambulance should be assigned to a hospital. The decision of assigning an ambulance to a hospital is based on the return policy. For the return policy, two options are considered. The first one is to carry the patient to a closest hospital. This policy does not take into account the load at the hospitals and may create long queues in some emergency service departments in hospitals. Therefore, we name this return policy as $non-communicating-return$ (NCR) policy. This policy is relevant when communication between the ambulance dispatcher and hospital emergency services can not take place. The second policy assumes that the ambulance dispatcher communicates with the emergency service departments and learns their queue lengths. Depending on the number of injuries and injury types in the queue, the travel time is increased for that hospital. Every severe, intermediate and light injury increases travel time by 60, 40 and 20 minutes, respectively, which are their respective mean treatment times in section. These adjusted travel times are compared, and the hospital with the smallest travel time is selected. We name this return policy a is $communicating - return$ (CR) policy.

3.11 First-treatment operations in the disaster locations

First-treatment operations are carried out in the disaster locations by ambulance medical units and this treatment is assumed to be exponentially distributed with mean of 10 minutes for each neighborhood.

3.12 The treatment times in the emergency rooms in the hospitals

Emergency room simulation is not performed in this simulation. Emergency room simulation requires steps like initial assessment, caring by a nurse, x-ray test etc., however in this simulation, these steps are aggregated, where we assumed that treatment times for each patient is exponentially distributed with a mean of 60 min for a severe injury, 40 min for an intermediate injury, and 20 min for a light injury. After a patient is served in the emergency, he or she gets out of the system. The simulation does not take into consideration of the beds in the hospitals other than emergency service beds.

3.13 Arrival of ambulance requests over time

The arrivals of calls to the call center is assumed to be Poisson distributed. Therefore, the interarrival times of calls are assumed to be exponentially distributed. The rates of exponential distribution for each neighborhood depend on the neighborhoods' populations and the expected percentage of destruction for each neighborhood, given in the JICA report [3]. In these calls, ambulances are requested. Especially in the first two days after the disaster strikes, many injured people are rescued from collapsed buildings and sometimes more than one ambulance may be requested to the disaster area by the same call. The batch request of ambulances is captured in the simulation through probability matrix in Table 1. This matrix is prepared by the comments of experts and AKUT [21].

The first 3-4 days after an earthquake is critically important for saving lives. The probability matrix that we used represents the changes in the arrival stream. This matrix assigns probabilities to batch arrivals. The probability of batch arrivals change in every two hours. Ambulance request calls are stationary, but by allowing batch arrivals, we are capturing the increase and decrease in the arrival numbers in different times. Rescue efforts are expected to reach their peak when soldiers and professional teams start to work effectively to rescue people from the collapsed buildings. By the probability matrix, arrival numbers could be at their highest values around 8 to 16 hours after disaster, especially after the professionals and soldiers start to work. By the time passes, number of people rescued in a unit time would eventually decrease, because the chances of survival of these people are getting lower. After two days, our model allows some calls for zero ambulance requests, that means these calls are not even made by the rescuers because nobody is rescued. In this simulation, batch arrivals may only occur in the first two days and the arrival process which means the rescuing of people under the collapsed buildings stops after about three days, because chance of survival almost decrease to zero.

There are two options considered for the arrival of calls. The first one is the instantaneous call when a patient or a batch of patients is rescued. In this case, when some injured people are rescued under the collapsed buildings, rescuers call the central call center in the same minute. Therefore, the information flow becomes almost instantaneous. The second option is periodic calls for every 15 minutes. The arrival process is still Poisson and still occurs with the same dynamics of the first option, but this time the transfer of information to the cental call center is delayed by at most 15 minutes.

3.14 Organization of data

There are four important entities that record critical data in the simulation. These are patient matrix and ambulance, hospital matrix, and bed matrix.

3.14.1 Patient matrix

Patient matrix records critical information for each patient. The number of the rows of the patient matrix is equal to the number of patients which differs in every replication of simulation. Each row carries information about a specific patient.

The number of columns is nine. The attributes of the patient matrix is as follows:

1) Patient ID: Each arrived patient is given a unique ID.

2) Patient Location ID: There are 99 neighborhoods considered in the simulation and each patient may be living in any one of these neighborhoods. The center of neighborhood assumption is considered for every casualty location.

3) Type of Injury: It is assumed that the rescuers who call for an ambulance request may able to categorize severe, middle, and light injuries.

4) States of a Patient: The state of the patient changes throughout the time. The states of a patient are listed as follows:

State 1: The patient arrives, and information comes to the central call center. Therefore patient is waiting for an ambulance but no ambulance is assigned to the patient yet.

State 2: An available ambulance has been assigned to the patient but the ambulance has not reached the patient yet.

State 3: The ambulance arrives to the patient, either is doing first treatment or is on the way to a hospital.

State 4: The patient is now in a hospital emergency room, but emergency room is full, therefore the patient is waiting in the queue.

State 5: The patient is now being served in a hospital emergency room (section 4.4).

State 6: The patient is out of the system. In this case, the patient is either healed or transferred to another department of a hospital.

5) Arrival Time: Arrival time depends on the Poisson arrival process and batch arrivals. Since we generate exponential random variables to represent the interarrival times, the arrival time can be generated as a continuous value (e.g., 156.54 mins). For the sake of simplicity, we round these values to the upper integer. For example, the arrival time of 156.54 mins is treated as 157 mins.

6) Hospital ID: It records the hospital ID in which the patient is treated.

7) System Out Time: It records the minute in which patient is out of the emergency room in a hospital.

8) Queuing in a Hospital: It records the waiting times of patients in a hospital. It could also be zero if patient starts to be treated immediately after the disaster.

9) Treatment Time in Emergency in a Hospital: Required treatment time for each patient is exponentially distributed with varying means, based on injury type.

3.14.2 Ambulance matrix

Ambulance matrix records critical information for each ambulance which is considered as a unique element in simulation. The number of the rows of the ambulance matrix is equal to the number of ambulances, which is assumed to be constant which is constant in the simulation. Each row carries information about a specific ambulance. The number of columns is nine. The attributes of the ambulance matrix is as follows:

1) State of the ambulance: The state of an ambulance changes throughout time. The states are listed as follows:

State 1: Ambulance is idle in a hospital, and ready for assigning to a patient.

State 2: Ambulance is assigned to a patient and on the way to this patient.

State 3: Ambulance picked up the patient, first treatment starts in the disaster location, and a decision must be made about which hospital should be the destination for this patient.

State 4: Ambulance is on the way to a hospital with a patient in it.

2) Hospital ID launched: It records hospital ID that the ambulance is launched. It is

important for calculating the travel time to a patient.

3) Patient ID: It records the ID of the patient that the ambulance is assigned.

4) Patient Location ID: It records the neighborhood ID of the patient. It is important for calculating the travel time to a patient.

5) Hospital ID Targeted: After a patient is picked up by the ambulance, a decision is done to carry the patient to a hospital. The decided hospital is recorded in this attribute.

6) Launch Time: It records the dispatching time of the ambulance from a hospital.

7) Arrival Time to the Patient: It records the arrival time of the ambulance to a patient.

8) Arrival Time to the Emergency Service Department: It records the arrival time of the ambulance to an emergency service department in a hospital.

9) Ambulance ID: Each ambulance has a unique ID.

3.14.3 Hospital matrix

Hospital matrix records critical information for each hospital. The number of the rows of the hospital matrix is equal to number of hospitals. Each row carries information about a specific hospital.

The number of columns is eight. The attributes of the hospital matrix is as follows:

1) State of the Hospital: Hospital is either full or there are empty beds.

2) Number of Beds in Emergency Service Department: The number of beds of an emergency service department of the hospital is recorded in this attribute.

3) Number of Busy Beds: It records the number of beds that are busy.

4) Number of Empty beds: It records the number of beds that are idle.

5) Number of Severe Injuries in the Queue.

6) Number of Medium Injuries in the Queue.

7) Number of Light Injuries in the Queue.

When a bed becomes idle, the first decision is to choose the severely injured person, who is waiting in the queue, in a first come first serve manner. If there is no severely injured person in the queue, then a moderately injured person is chosen in a first come first serve manner. If there is no severely injured or moderately injured person in the queue, a lightly injured person is chosen to be treated.

8) Hospital ID: Each Hospital has a unique ID.

3.14.4 Bed matrix

Bed matrix records critical information for each bed in each hospital emergency department. The number of the rows of the bed matrix is equal to the number of total emergency department beds. Each row carries information about a specific bed. The number of columns is seven. The attributes of the bed matrix is as follows:

1) State of the Bed: The bed is either occupied or idle.

2) Hospital ID: Hospital ID that the bed is located.

3) Patient ID: It records the patient ID that is currently served by the bed.

4) Starting time: It records starting time of the treatment process.

5) End time: It records ending time of the treatment process.

6) Serving Duration: It records the required treatment time of this specific patient.

7) Bed ID: It records the unique ID of the bed.

3.15 Simulation State Changes

In this section, working principles of the simulation are explained within a unit time of minute.

Processes are numbered.

In every minute:

time=t;

1) Check the patients that are in state 0.

If t is greater than the arrival time of a patient

Patient is arrived and requesting an ambulance. Switch the state of the patient to state 1.

Repeat process 1 for the patients that are in state 0.

2) Check the patients that are in state 1.

If there is at least one patient in state 1, check the ambulances that are in state 1.

If there is at least one ambulance in state 1, assign a patient with an ambulance based on dispatching policy. Now ambulance is on the way to the patient. Switch the states of the ambulance and the patient to 2.

Repeat process 2 until either there are no idle ambulances left or there are no ambulance request.

3) Check the ambulances that are in state 2

If arrival time to the patient is greater than t

Change the state of the ambulance to 3. Now ambulance is arrived to the patient location and waiting for the decision to which hospital to target based on the return policy. Start the first-treatment of patient in the disaster location.

Repeat process 3 for all the ambulances that are in state 2.

4) Check the ambulances that are in state 3

If first-treatment of the assigned patient finishes

Assign the ambulance to a hospital based on return policy. Now the ambulance is carrying the patient to a hospital. Change ambulance state to state 4. Change patient state to state 3.

Repeat process 4 for all the ambulances that are in state 3.

5) Check the number of ambulances that are in state 4.

If t is greater than arrival time to the emergency service department

Ambulance arrived to the emergency service department of a hospital and unload the patient. Change the state of the patient to state 4, change the state of the ambulance to state 1.

If empty beds in the emergency ¿ 0, the patient starts to be served immediately. Change the bed state from state 1 to 2. Change the patient state from 4 to 5.

Else if empty beds in the emergency = 0, the patient enters the queue.

Repeat process 5 for all the ambulances that are in state 4.

6) Check beds that are in state 2.

If t is greater than end time of serve

The patient is treated in the emergency service department and either transferred to other departments in the hospital or the patient gets out of hospital. Change the state of the patient to state 6. Change the state of the patient to state 1.

Repeat process 6 for all the beds that are in state 2.

The other attributes of the patient matrix, ambulance matrix, hospital matrix and bed matrix are updated for each unit as the name of the attributes suggest.

3.16 Verification and validation

The simulation model is tested and verified by altering various parameters in several different trials. The consistency is assured in each trial. For example, while new ambulances are added to the emergency medical system in Section 4.6, consistency is assured and every addition causes the $\overline{RTH}$ time to get lower. The expected earthquake for Istanbul is a strong earthquake and in Istanbul, an earthquake with similar strength has happened in the eighteenth century. From that time on, the population of the city has increased dramatically and building types have changed. It is impossible to compare the expected earthquake with the previous earthquakes. Moreover, the damage of an earthquake is different depending on geological locations of the cities, thus it is not correct to validate this simulation with an earthquake that has happened in another city. Therefore, validation can not be done exactly. The best source for the expected damages is the JICA report [3], and we try to be consistent with this report in our study for the validation. For arrival number validation, JICA report has expected casualty numbers for the districts but not for the neighborhoods, therefore we try to match casualty numbers with JICA report in the process defined in Section 3.4.

3.17 Confidence intervals

Replication number is set to 100, which guarantees decreasing the confidence intervals and standard deviations to a low level. 48 instances are tested depending on dispatching policies, arrival amounts, information types, return policies and velocities. The determining mean is the $\overline{RTH}$ for all patients. Standard deviation is calculated among replications. Confidence intervals for both $\overline{RTH}$ and standard deviations are reported. Instance code is just a code for differentiating the simulation runs which uses different parameters. Some of the instances' $\overline{RTH}$, standard deviations and confidence intervals for RTH are as follows:

Table 3.1: Confidence intervals

instance code	mean	std. deviation	conf. int. lower mean	conf. int. upper mean
121222	1363.80	37.77	1353.10	1374.60
221222	2689.50	24.90	2682.40	2696.60
321222	1101.60	43.52	1089.30	1114.00

It is observed that confidence intervals for 50 replications are already very small, thus replicating the simulation for 50 times seems quiet enough to report the results.

This simulation is not a steady state simulation; rather it is a terminating simulation. For example, arrival stream is continuously changing during the five days after the disaster strikes.

Chapter 4

PERFORMANCE EVALUATION OF DISPATCHING POLICIES BY SIMULATION EXPERIMENTS

The current emergency medical system in seven districts (Bahçelievler, Güngören, Zeytinburnu, Bağcılar, Esenler, Bayrampaşa and Bakırköy) of Istanbul contains 18 hospitals and 128 ambulances located in these hospitals as reported in [1]. We use two main performance criteria while comparing the policies. First one is average response time to patients which is estimated by average rescue-to-hospital time $\overline{RTH}$ (or average rescue-to-transfer time $\overline{RTH}$). Second one is the service level (SL1 for RTH based service level, SL2 for RTT based service level). Both performance criteria are also estimated for neighborhoods. The tested ambulance dispatching policies are first-called-first-served (FCFS), shortest-distance-first (SDF), and most-critical-patients-first (MCPF). In all sections, NCR policy is used as a return policy, however in Section 4.4, the results of the CR policy is presented.

The simulation model runs under two main main assumptions. First, patients will wait for the ambulances as long as it takes without being transported by any other vehicle. Second, the dispacther does not reject any of the ambulance requests. As a result, it is possible that a patient waits for several days to be picked up by an ambulance but most of the patients will eventually be taken to a hospital. Therefore, the numbers are sometimes very high compared to real-life case, but these results show the worst case situations and implementation options.

This chapter is organized as follows. Section 4.1 explains the results for the real-time information update case. The other sections provide comparisons with the results presented in Section 4.1. Section 4.2 provides results of the periodic information update case. In Section 4.3, the effects of changing mean travel times are investigated. In Section 4.4, communication between hospital emergency service coordinators and ambulance drivers are taken into consideration (CR return policy is considered). Section 4.5 discusses the consequences of adding temporary emergency hospitals (TEH) after the disaster. Section 4.6 illustrates the outcome of adding ambulances to the emergency system.

The simulation runs are performed via MATLAB R2008a software. The processor of the computer is Intel(R) Core(TM) i7 CPU 920 @ 2.67 GHz, 6 GB RAM, 64 bit. One run (50 replication) takes between 1 hour and 10 hours depending on the the load of the parameters.

4.1 Real-time information update case

The underlying assumption in this case is the availability of real-time information on the status of patients and ambulances including their locations. When a patient is rescued, this information is conveyed to the dispatcher. In daily life, typically the FCFS policy is implemented because ambulance requests are sparse. However, in a post-disaster environment, ambulance units would be overwhelmed by the massive number of ambulance requests.

The $\overline{RTH}$ and $\overline{RTT}$ values of FCFS policy are so close (Table 4.1). But both of the values are very high compared to other policies. The reason is that, ambulances could sometimes travel a very long distance in order to serve the first-called patient in FCFS policy. In Table 4.2, $\overline{SL1}$ (service level based on $\overline{RTH}$) and $\overline{SL2}$ (service level based on $\overline{RTT}$) values of each three dispatching policies are presented. FCFS policy results in 0.733 and 0.471 for overall $\overline{SL1}$ and $\overline{SL2}$ which are quite poor service levels compared to other policies. On the other side, SDF policy results in better service time for both $\overline{RTH}$ and $\overline{RTT}$ (4.1). But, it is noteworthy that there is a large gap between $\overline{RTH}$ and $\overline{RTT}$. This gap is caused by inefficient use of resources. By inefficient use of resources, we mean inefficient assignment of ambulances to hospitals. Using return policy of NCR results in 100 percent of the patients to be carried to the hospitals in five days, which is showed by $SL1$ value in Table 4.2. Although the overall $\overline{SL1}$ value is perfect for SDF policy, overall $\overline{SL2}$ value is just 0.539. This indicates that, there are long queues in some hospital emergency departments and while in some hospitals, these departments remain idle due to NCR return policy. The result of this situation is high $\overline{RTT}$ and low $\overline{SL2}$.

MCPF policy can only be implemented when the rescue teams have the capability to classify the injuries of the patients into three types. This policy results in 23.8 percent higher $\overline{RTH}$ and 11.8 percent higher $\overline{RTT}$ than SDF policy (Table 4.1). Overall service levels are similar between these two policies and both of them have perfect $\overline{SL1}$ and MCPF policy has 1.7 percent better overall $\overline{SL2}$ than SDF policy with 0.548 (Table 4.2). This is still not a good service level, but MCPF policy greatly reduces the served severely injured patients' $\overline{RTH}$ and $\overline{RTT}$ values which are 283 minutes and 1217.4 minutes (Table 4.1). The direct result of this situation is the saving of severely injured people quicker than the other patients which would be crucial in a post-disaster environment.

Table 4.1: $\overline{RTH}$ and $\overline{RTT}$ values of each three dispatching policies with NCR return policy

Average RTH and RTT values	FCFS policy	SDF policy	MCPF policy
Overall average RTH (min)	2689.5	1101.6	1363.8
Overall average RTT (min)	2765.4	1836.6	2052.9
Type 1 average RTH (min)	2689.8	1102.3	283.0
Type 1 average RTT (min)	2771.8	1844.5	1217.4
Type 2 average RTH (min)	2687.5	1100.6	2643.3
Type 2 average RTT (min)	2757.3	1829.5	3026.5
Type 3 average RTH (min)	2693.6	1100.5	4032.8
Type 3 average RTT (min)	2750.9	1809.9	4264.6

When we investigate the $\overline{RTH}(j)$ values for each neighborhood j under FCFS dispatching policy with NCR return policy, we obtain values ranging from 2400 to 2900 min for each neighborhood in Figure 4.1. we see that FCFS policy results in very high values for a majority of the neighborhoods. Moreover, the $\overline{SL1}(j)$ value for each neighborhood j is around 0.73 for all neighborhoods except some of them. This indicates that FCFS dispatching policy results in very poor service, given the current ambulance and hospital resources.

SDF policy results in better overall $\overline{RTH}$ and $\overline{RTT}$ values and service levels than FCFS

Table 4.2: $\overline{SL1}$ (service level based on $\overline{RTH}$) and $\overline{SL2}$ (service level based on $\overline{RTT}$) values of each three dispatching policies with NCR return policy

Service Levels	FCFS policy	SDF policy	MCPF policy
Overall service level, RTH based	0.733	1.000	1.000
Overall service level, RTT based	0.471	0.539	0.548
Type 1 service level, RTH based	0.733	1.000	1.000
Type 1 service level, RTT based	0.470	0.539	0.552
Type 2 service level, RTH based	0.732	1.000	1.000
Type 2 service level, RTT based	0.471	0.539	0.541
Type 3 service level, RTH based	0.734	1.000	1.000
Type 3 service level, RTT based	0.473	0.541	0.542

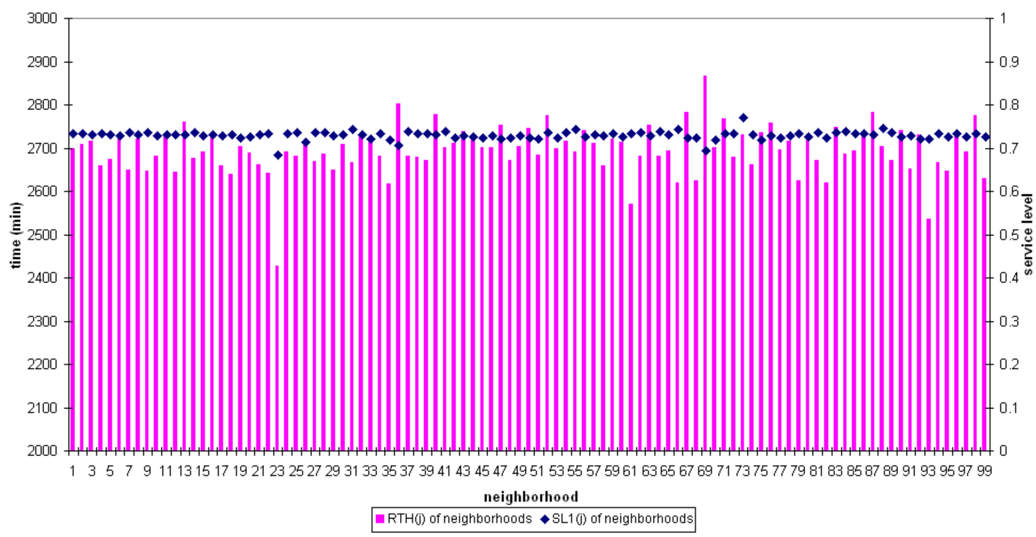

Figure 4.1: FCFS dispatching policy with NCR return policy: $\overline{RTH}(j)$ and $\overline{SL1}(j)$ of neighborhoods

policy (Figure 4.2). However, when we compare neighborboods based on $\overline{RTH}$, we see that some neighborhoods have very large response times although $\overline{SL1}$ is perfect for this policy. This creates a social issue and the neighborhoods which are close to ambulances becomes lucky while some other neighborhoods are very unlucky. This situation may be overcome by adding additional emergency hospitals and ambulances to these neighborhoods as investigated in Section 4.5 and Section 4.6. When we compare $\overline{SL2}(j)$ value for each neighborhood j for SDF policy, we observe that while neighborhoods have 100 percent service levels with either high or low $\overline{RTT}(j)$ values depending on their distance to hospitals, some neighborhoods have service levels almost zero. For some neigborhoods, very few people could be transferred out of emergency service because they wait in long queues in emergency departments.

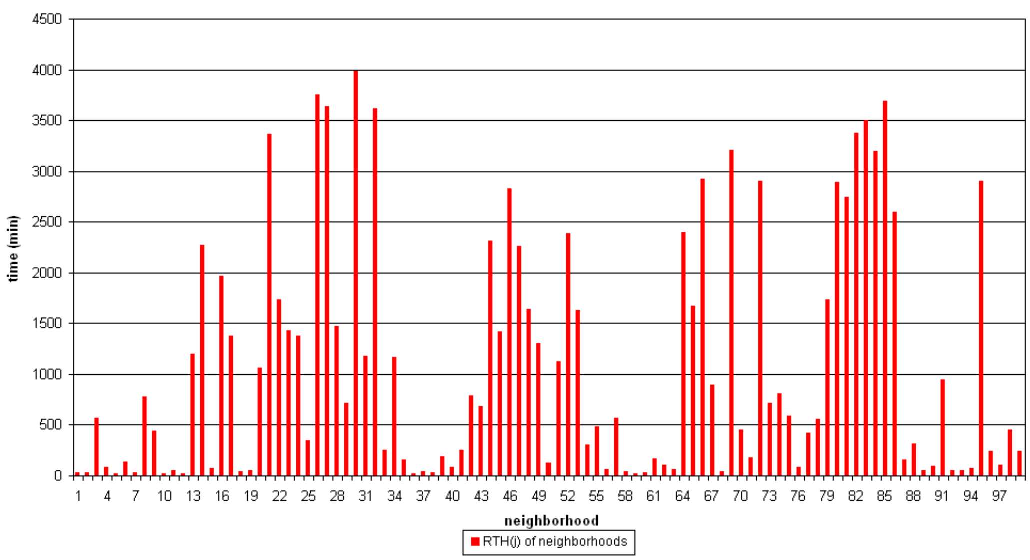

Figure 4.2: SDF dispatching policy with NCR return policy: $\overline{RTH}(j)$ of neighborhoods

Figure 4.4 shows the $\overline{RTH}(j)$ and $\overline{RTT}(j)$ of neighborhoods of MCPF policy. It is observed that MCPF policy treats neighborhoods more fairly than SDF policy based on $\overline{RTH}(j)$ values. On the other side, $\overline{RTT}(j)$ values of neighborhoods vary a lot. Some

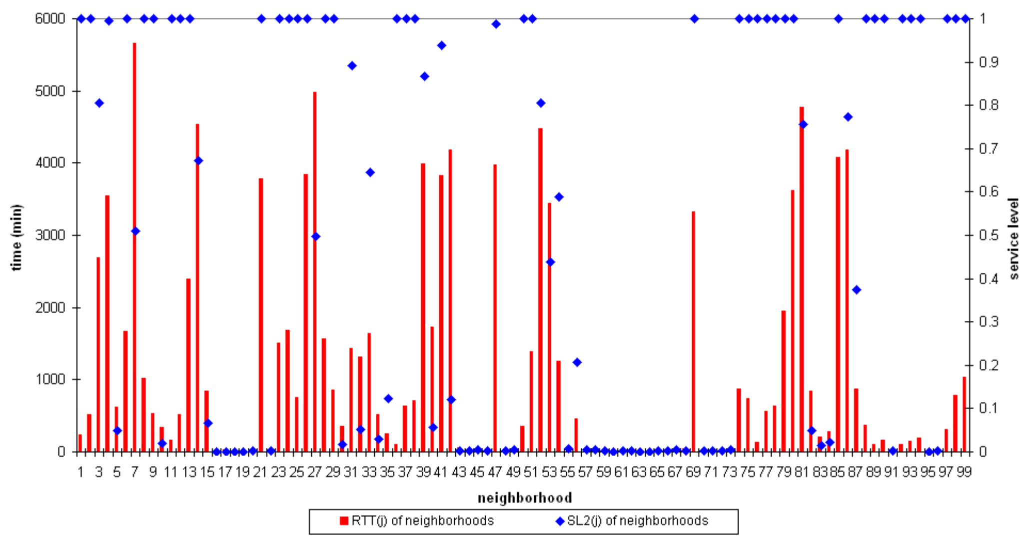

Figure 4.3: SDF dispatching policy with NCR return policy: $\overline{RTT}(j)$ and $\overline{SL2}(j)$ of neighborhoods

neighborhoods have very low $\overline{RTT}(j)$ values which seems to be a very good result but it is not the case. The neighborhoods which have smaller $\overline{RTT}(j)$ values have actually very poor $\overline{SL2}(j)$ levels (Figure 4.5). Some patients are stuck in the queue and can not be served. The reason of this situation is that, tie breaker of the MCPF policy is SDF policy. We also implemented MCPF policy with FCFS policy as a tie breaker policy, but the results are only 0.5 percent different than FCFS policy which are still quite bad so we did not publish those results.

MCPF policy has a certain advantage over SDF policy by saving more severe injured patients in shorter amount of time. This fact is illustrated for the neighborhoods in Figure 4.6. From Table 4.1, we know that $\overline{SL1}$ is 1.000, which means that all the patients are carried to hospitals in five days. Figure 4.6 shows that MCPF policy has very low service times for type 1 injuries based on $\overline{RTH}(j)$ for each neighborhood j. The results of this policy indicate that; if all rescue team members are educated for triage before earthquake, the response to the overwhelming injuries could be a lot more effective by assigning ambulances

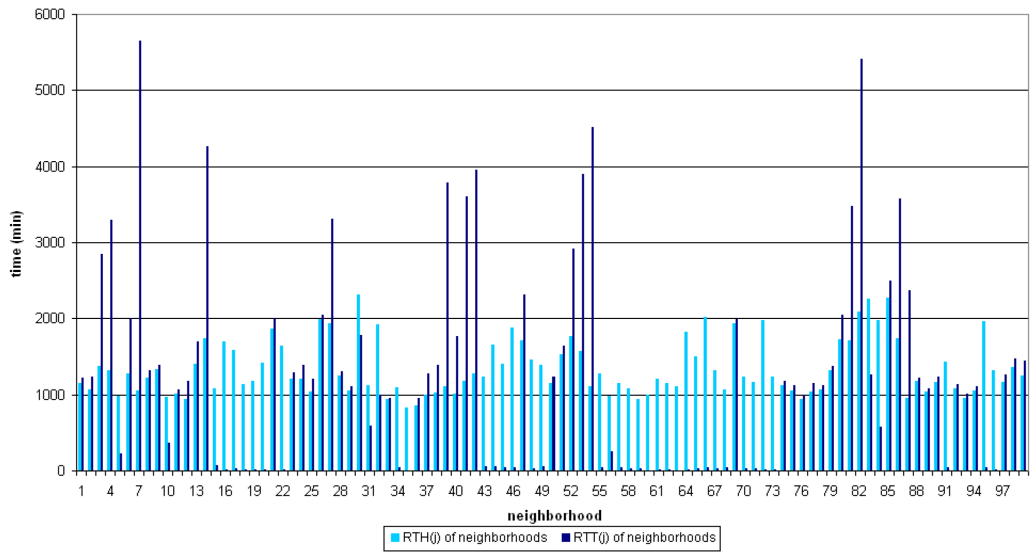

Figure 4.4: MCPF dispatching policy with NCR return policy: $\overline{RTH}(j)$ and $\overline{RTT}(j)$ of neighborhoods

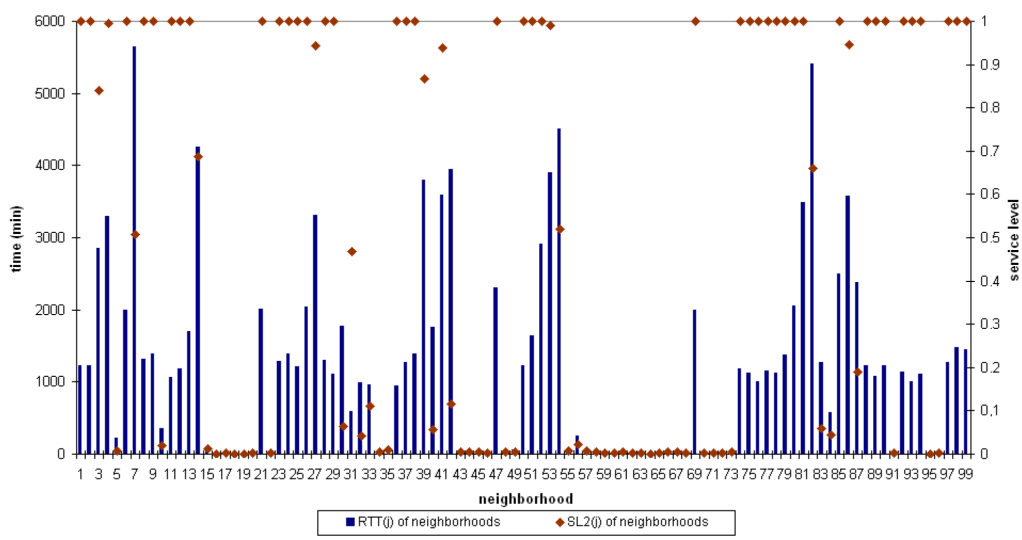

Figure 4.5: MCPF dispatching policy with NCR return policy: $\overline{RTT}(j)$ and $\overline{SL2}(j)$ of neighborhoods

to the severe injuries first.

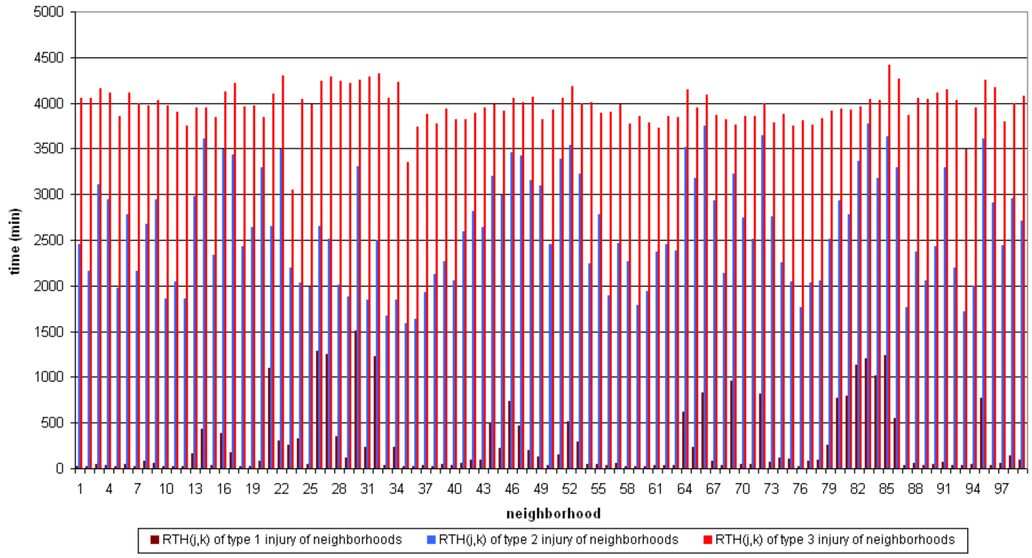

Figure 4.6: MCPF dispatching policy with NCR return policy: Comparison of $\overline{RTT}(j,k)$ of neighborhoods

Figure 4.7 shows the SDF policy results ($\overline{RTH}(j)$ of each neighborhood j). The map shows the average service times in neighborhoods of seven districts that are studied, according to the legend. The darker colors indicate longer $\overline{RTH}(j)$ value for each neighborhood j while lighter colors indicate smaller $\overline{RTH}(j)$ values. This map provides a better view to see the neighborhoods that are served in shorter service times or longer service times.

4.2 Periodic information update case

In a post-disaster environment, real-time information update may not be possible due to communication difficulties or organizational problems. Furthermore, coordinating the information flow with periodic updates to a disaster coordination center is more likely to be implemented after a disaster instead of real-time information update. Therefore, in this section, we assume that rescuers make the calls to request ambulances for the discovered

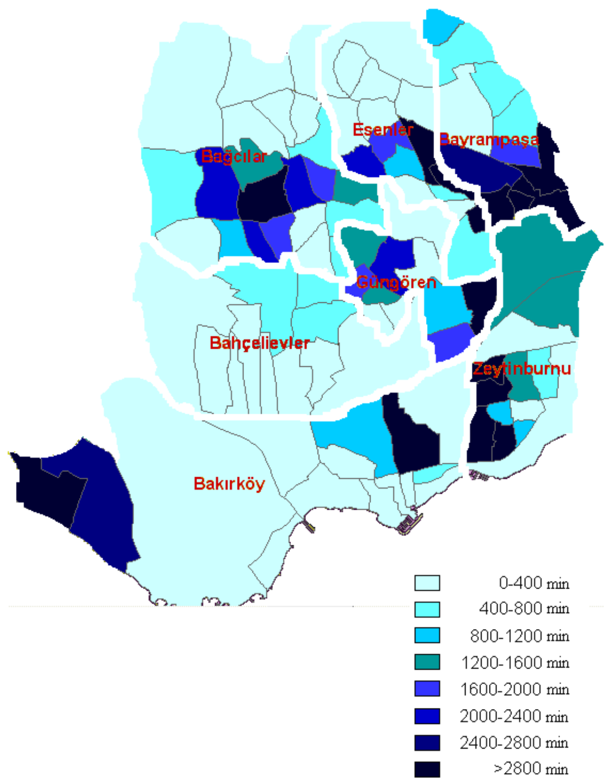

Figure 4.7: Map view of $\overline{RTH}(j)$ values of neighborhoods under SDF policy

patients every 30 minutes, and request ambulances based on the number of arrivals during the previous 30 minutes.

Again, FCFS is the worst policy for $\overline{RTH}$ and SDF policy is the best for $\overline{RTH}$ (Table 4.3). The results of the MCPF policy is slightly improved compared to real-time information update because in 30 minutes, there is a chance that no type 1 injury will be left to serve and there is a good chance that nearby type 2 or type 4 patients are served so that ambulances travel less distance. Therefore, although the service times of $\overline{RTH}$ of overall, type 2 and type 3 are improved, type 1 service level worsen slightly

Service levels of periodic information update case is almost identical with real-time information update case (Table 4.4). Overall $\overline{SL1}$ and $\overline{SL2}$ values of periodic information update case are 0.678 and 0.450 respectively while in real-time information update case, these service levels are 0.733 and 0.471 respectively.

The results indicate that 30-min periodic information update does not differ too much from real-time information update case. Therefore, implementing periodic information update system is also effective in responding to ambulans request calls. Moreover, implementing periodic information update is a lot more easier than implementing real-time information update.

Table 4.3: Comparison of real-time information update and 30-min periodic information update cases with $\overline{RTH}$ and $\overline{RTT}$ values of each three dispatching policies with NCR return policy

Real-time vs. Periodic Average RTH and RTT values	Real-time FCFS policy	Periodic FCFS policy	Real-time SDF policy	Periodic SDF policy	Real-time MCPF policy	Periodic MCPF policy
Overall average RTH (min)	2689.5	2774.3	1101.6	1108.0	1363.8	1326.8
Overall average RTT (min)	2765.4	2846.5	1836.6	1823.9	2052.9	2041.4
Type 1 average RTH (min)	2689.8	2775.6	1102.3	1108.7	283.0	295.6
Type 1 average RTT (min)	2771.8	2853.7	1844.5	1830.9	1217.4	1242.3
Type 2 average RTH (min)	2687.5	2770.6	1100.6	1106.6	2643.3	2534.1
Type 2 average RTT (min)	2757.3	2838.1	1829.5	1817.7	3026.5	2973.7
Type 3 average RTH (min)	2693.6	2777.4	1100.5	1107.6	4032.8	3913.1
Type 3 average RTT (min)	2750.9	2828.0	1809.9	1799.9	4264.6	4141.7

Table 4.4: Comparison of real-time information update and 30-min periodic information update cases with $\overline{SL1}$ and $\overline{SL2}$ values of each three dispatching policies with NCR return policy

Real-time vs. Periodic Service Levels	Real-time FCFS policy	Periodic FCFS policy	Real-time SDF policy	Periodic SDF policy	Real-time MCPF policy	Periodic MCPF policy
Overall service level, RTH based	0.733	0.678	1.000	1.000	1.000	1.000
Overall service level, RTT based	0.471	0.450	0.539	0.539	0.548	0.547
Type 1 service level, RTH based	0.733	0.678	1.000	1.000	1.000	1.000
Type 1 service level, RTT based	0.470	0.449	0.539	0.539	0.552	0.551
Type 2 service level, RTH based	0.732	0.677	1.000	1.000	1.000	1.000
Type 2 service level, RTT based	0.471	0.450	0.539	0.539	0.541	0.541
Type 3 service level, RTH based	0.734	0.678	1.000	1.000	1.000	1.000
Type 3 service level, RTT based	0.473	0.451	0.541	0.541	0.542	0.542

4.3 The effects of increased velocity of ambulances

This section covers the effects of increased velocity of ambulances. This section analyzes decreasing travel times by increasing velocities to account for more optimistic road conditions.

Increasing maximum of expected average velocity from 25 km/h to 35 km/h has some implications. When the isolation risks of neighborhoods are added to the travel times calculations, the travel times become too high. One way to consider 25 km/h as a worst case scenario. It is worthwhile to analyze a more optimistic scenario for comparison purposes. The direct result of this policy is to increase minimum average velocity from 6.25 km/h to 8.75 km/h.

After an earthquake, many people will try to reach their relatives or evacuate the area. Furthermore, some roads will be damaged or blocked. Therefore, traffic jam is expected on some of the streets. Hence, it is very difficult to predict post-earthquake travel times. We assume that travel times are random with exponential distribution. Considering that people are willing to open a lane to an ambulance, most of the time, an ambulance's average velocity is higher than the speed of other vehicles in the traffic. This section analyzes the what-if question of increasing ambulance velocity. The other conditions are identical with Section 4.1.

The results in Table 4.5 indicate that, 40 percent increase in average velocity causes 18.6, 40.4 and 44.3 percent improvement in FCFS, SDF and MCPF policies based on $\overline{RTH}$. For $\overline{RTT}$, improvement becomes 16.0, 6.7 and 11.8 percent. Although the improvement in SDF and MCPF policies for $\overline{RTH}$ is noticable, the improvement for $\overline{RTT}$ is not so high. The reason could be the NCR return policy. In this return policy, it is inevitable to observe long queues in some hospitals while others are underutilized.

Table 4.5: Comparison of 25 km/h and 35 km/h travel velocities of ambulances with $\overline{RTH}$ and $\overline{RTT}$ values of each three dispatching policies with NCR return policy

Increased velocity effect (NCR)	25 km/h	35 km/h	25 km/h	35 km/h	25 km/h	35 km/h
Average RTH and RTT values	FCFS policy	FCFS policy	SDF policy	SDF policy	MCPF policy	MCPF policy
Overall average RTH (min)	2689.5	2268.2	1101.6	784.0	1363.8	944.1
Overall average RTT (min)	2765.4	2383.5	1836.6	1720.7	2052.9	1835.2
Type 1 average RTH (min)	2689.8	2268.3	1102.3	785.1	283.0	144.8
Type 1 average RTT (min)	2771.8	2390.9	1844.5	1728.6	1217.4	1282.2
Type 2 average RTH (min)	2687.5	2268.4	1100.6	782.3	2643.3	1833.8
Type 2 average RTT (min)	2757.3	2376.8	1829.5	1712.6	3026.5	2418.6
Type 3 average RTH (min)	2693.6	2267.1	1100.5	782.5	4032.8	3087.7
Type 3 average RTT (min)	2750.9	2359.6	1809.9	1698.1	4264.6	3439.0

Table 4.6: Comparison of 25 km/h and 35 km/h travel velocities of ambulances with $\overline{SL1}$ and $\overline{SL2}$ values of each three dispatching policies with NCR return policy

Increased velocity effect (NCR)	25 km/h	35 km/h	25 km/h	35 km/h	25 km/h	35 km/h
Service Levels	FCFS policy	FCFS policy	SDF policy	SDF policy	MCPF policy	MCPF policy
Overall service level, RTH based	0.733	0.962	1.000	1.000	1.000	1.000
Overall service level, RTT based	0.471	0.538	0.539	0.546	0.548	0.550
Type 1 service level, RTH based	0.733	0.962	1.000	1.000	1.000	1.000
Type 1 service level, RTT based	0.470	0.537	0.539	0.545	0.552	0.552
Type 2 service level, RTH based	0.732	0.963	1.000	1.000	1.000	1.000
Type 2 service level, RTT based	0.471	0.539	0.539	0.546	0.541	0.547
Type 3 service level, RTH based	0.734	0.962	1.000	1.000	1.000	1.000
Type 3 service level, RTT based	0.473	0.541	0.541	0.549	0.542	0.549

4.4 The effects of communication on service times and service levels

In this section, the effects of communication between ambulance drivers and hospital coordinators are tested via simulation model. It is not a part of this study to simulate the periods inside hospital emergency service departments where patients go through different diagnosis and treatment procedures depending on conditions. Several studies including Duguay and Chetouane [22] simulate the emergency service during daily operations, rather than a mass casualty incident. This paper could be a reference point while integrating ambulance dispatching and emergency service operations in the simulation. Carrying the patients to the hospitals with shortest expected travel times (NCR) without taking into consideration the current loads at the hospitals could lead to very long queues in some hospitals, while others could be underutilized. In this study, a random total service duration is assumed for hospital emergency bed service. The service times in the hospital emergency departments are exponentially distributed with means 60, 40 and 20 minutes for are severe, moderate and light injuries, respectively. We obtained the hospital emergency bed capacities from [1].

In this section, we consider the availability of communication between the dispatcher, ambulance driver and hospital emergency service units. If the ambulance drivers' can learn the queue lengths in the hospitals, patients can be transported to nearby hospitals with less queue length. Hence, we propose an ambulance return policy that utilizes this information.

When the dispatcher obtains information on the queue sizes in the emergency service units in hospitals, drivers may be directed to the nearby hospitals with small queue lengths. In the simulation model, the expected treatment times of the patients in the queues at the hospitals are added to the expected travel times. Then the closest hospital with respect to this adjusted duration is selected as the ambulance destination. This return policy is named $communicating - return$ (CR) policy.

Table 4.7 compares NCR and CR return policies with $\overline{RTH}$ and $\overline{RTT}$ values of each three dispatching policies. We observe that overall $\overline{RTH}$ get worse dramatically, but overall $\overline{RTT}$ values get worse slightly for SDF and MCPF policies. But when we compare service levels, although $\overline{SL1}$ decreased from 1.000 to 0.867 and 0.804 for SDF and MCPF policy respectively, $\overline{SL2}$ values improve dramatically from 0.539 to 0.855 for SDF and from 0.548 to 0.795 for MCPF by using CR return policy Table 4.8 . By using this return policy, ambulances spend more time after taking the patient from disaster location until reaching to hospitals, but patients who arrive to hospitals do not wait in long queues in the emergency departments, rather they are started to be served immediately or wait for a few minutes. Moreover, the resources of hospital emergency departments are utilized more effectively compared to NCR policy. It is also very important to notice that it is possible to save all the severely injured people both by RTH or RTT measure by using MCPF policy. $SL2$ of type2 injuries are also increased. The outcome of implementing MCPF policy with CR policy is that, type3 injures are almost ignored and only 0.7 percent of them are served. SDF policy is still the best for overall $\overline{RTH}$, $\overline{RTT}$, $\overline{SL1}$ and $\overline{SL2}$ values by implementing CR return policy. FCFS policy results are improved for CR return policy from NCR return policy, but still the worst policy to be implemented. The results of Table 4.7 and Table 4.8 indicate that carrying the patients to the nearest hospitals without communication is not a logical approach due to ineffective usage of hospital emergency departments and long queues. Therefore, intensive communication between ambulance drivers and hospital coordinators is necessary in a post-disaster environment.

Table 4.7: Real-time information update case: Comparison of NCR and CR return policies with $\overline{RTH}$ and $\overline{RTT}$ values of each three dispatching policies

Return policies: NCR vs. CR	NCR	CR	NCR	CR	NCR	CR
Average RTH and RTT values	FCFS policy	FCFS policy	SDF policy	SDF policy	MCPF policy	MCPF policy
Overall average RTH (min)	2689.5	2816.1	1101.6	1883.3	1363.8	2093.1
Overall average RTT (min)	2765.4	2854.8	1836.6	1943.0	2052.9	2185.5
Type 1 average RTH (min)	2689.8	2816.4	1102.3	1882.5	283.0	1155.2
Type 1 average RTT (min)	2771.8	2861.3	1844.5	1948.3	1217.4	1298.0
Type 2 average RTH (min)	2687.5	2814.9	1100.6	1887.7	2643.3	4890.5
Type 2 average RTT (min)	2757.3	2847.1	1829.5	1942.0	3026.5	4954.6
Type 3 average RTH (min)	2693.6	2817.1	1100.5	1875.1	4032.8	37.9
Type 3 average RTT (min)	2750.9	2838.6	1809.9	1913.8	4264.6	73.8

Figure 4.8 shows the results of implementing FCFS policy with CR return policy. It is

Table 4.8: Real-time information update case: Comparison of NCR and CR return policies with $\overline{SL1}$ and $\overline{SL2}$ values of each three dispatching policies

Return policies: NCR vs. CR	NCR	CR	NCR	CR	NCR	CR
Service Levels	FCFS policy	FCFS policy	SDF policy	SDF policy	MCPF policy	MCPF policy
Overall service level, RTH based	0.733	0.632	1.000	0.867	1.000	0.804
Overall service level, RTT based	0.471	0.626	0.539	0.855	0.548	0.795
Type 1 service level, RTH based	0.733	0.632	1.000	0.867	1.000	1.000
Type 1 service level, RTT based	0.470	0.626	0.539	0.854	0.552	1.000
Type 2 service level, RTH based	0.732	0.632	1.000	0.867	1.000	0.675
Type 2 service level, RTT based	0.471	0.627	0.539	0.856	0.541	0.646
Type 3 service level, RTH based	0.734	0.632	1.000	0.866	1.000	0.007
Type 3 service level, RTT based	0.473	0.630	0.541	0.857	0.542	0.007

observed that overall $\overline{RTH}(j)$ and $\overline{RTT}(j)$ of each neighborhood j are close to each other, but these response times are high. Service levels are also similar both with other and among the neighborhoods. This policy can be seen as the most fair policy among neighborhoods, however it is a bad policy with poor response times and poor service levels. Figure 4.9 shows the outcome of implementing SDF policy with CR return policy. Service levels are perfect some neighborhoods, however some of them has very poor service levels. Response times vary between neighborhoods and some of them has average of more than 5000 minutes. The standard deviation of average response times of neighborhoods is so high and this fact will probably create a social problem if this policy is implemented after a disaster. Figure 4.10 displays the results of MCPF policy with CR return policy. In this figure, service levels of neighborhoods range between 0.6 and 0.92. Overall average of 0.8 service level is a good result and Table 4.7 indicates that all the severely injured people are served. Moreover, average response times of the neighborhoods are not too different as it was in SDF policy which satisfies social fairness better. This policy arises as a very good alternative to SDF policy when using CR as a return policy.

Table 4.9 and Table 4.10 display the results of periodic information case with CR return policy. They are very similar to Table 4.7 and Table 4.8. This indicates that using a real-time information update system or 30-min periodic update system does not make a noticable difference with CR or NCR return policies.

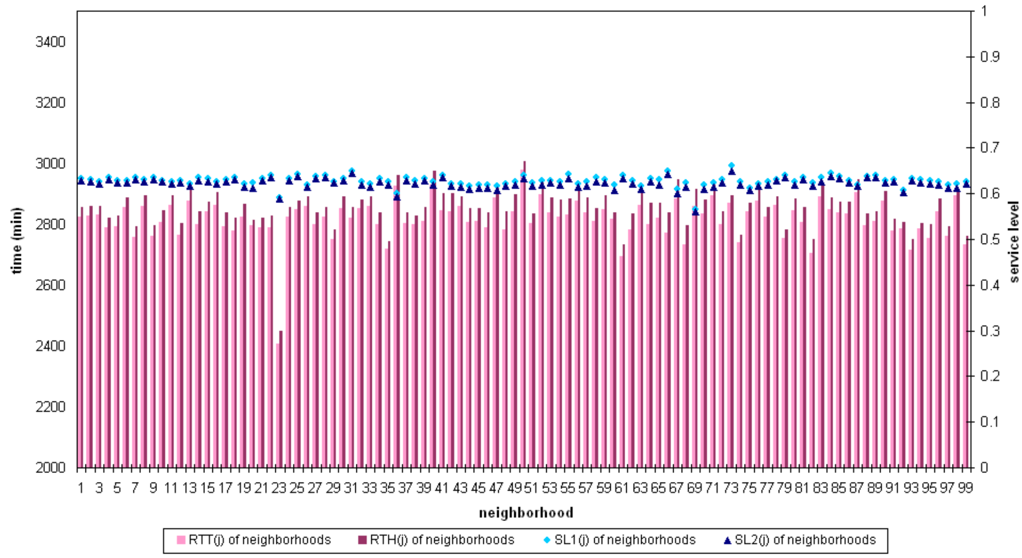

Figure 4.8: FCFS dispatching policy with CR return policy: $\overline{RTH}(j)$, $\overline{RTT}(j)$, $\overline{SL1}(j)$ and $\overline{SL2}(j)$ of neighborhoods

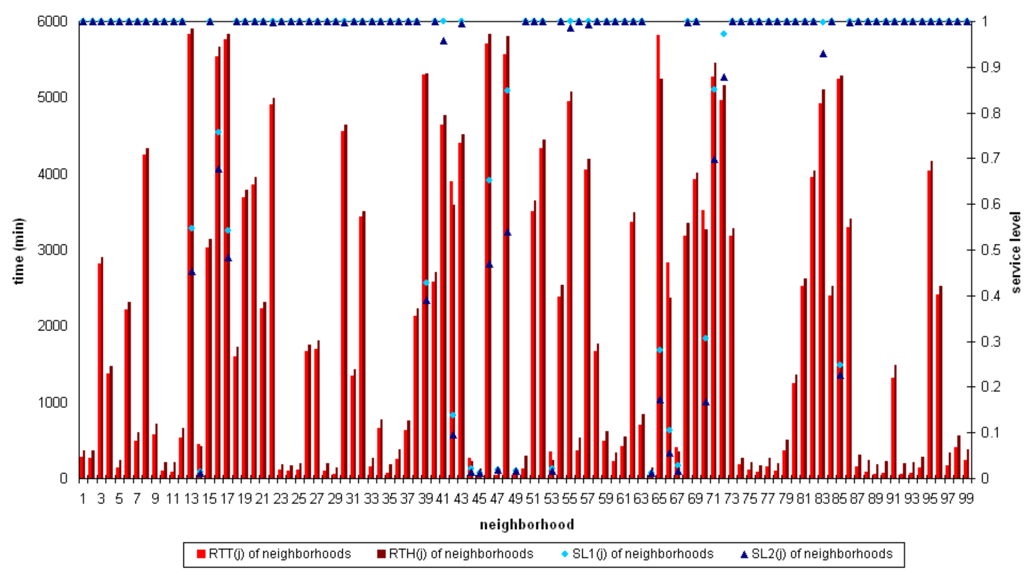

Figure 4.9: SDF dispatching policy with CR return policy: $\overline{RTH}(j)$, $\overline{RTT}(j)$, $\overline{SL1}(j)$ and $\overline{SL2}(j)$ of neighborhoods

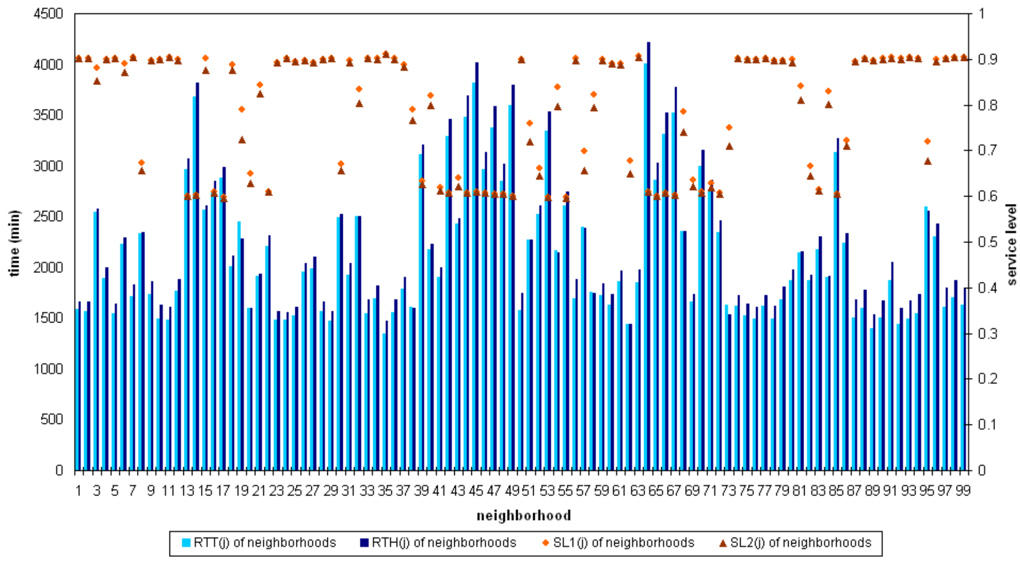

Figure 4.10: MCPF dispatching policy with CR return policy: $\overline{RTH}(j)$, $\overline{RTT}(j)$, $\overline{SL1}(j)$ and $\overline{SL2}(j)$ of neighborhoods

Table 4.9: Periodic information update case: Comparison of NCR and CR return policies with $\overline{RTH}$ and $\overline{RTT}$ values of each three dispatching policies

Real-time vs. Periodic (CR)	Real-time	Periodic	Real-time	Periodic	Real-time	Periodic
Average RTH and RTT values	FCFS policy	FCFS policy	SDF policy	SDF policy	MCPF policy	MCPF policy
Overall average RTH (min)	2816.1	2867.1	1883.3	1893.5	2093.1	2098.0
Overall average RTT (min)	2854.8	2911.6	1943.0	1955.7	2185.5	2191.3
Type 1 average RTH (min)	2816.4	2867.7	1882.5	1892.7	1155.2	1178.8
Type 1 average RTT (min)	2861.3	2918.5	1948.3	1961.3	1298.0	1323.3
Type 2 average RTH (min)	2814.9	2864.9	1887.7	1898.4	4890.5	4850.3
Type 2 average RTT (min)	2847.1	2902.9	1942.0	1953.7	4954.6	4910.9
Type 3 average RTH (min)	2817.1	2869.5	1875.1	1883.6	37.9	74.4
Type 3 average RTT (min)	2838.6	2896.4	1913.8	1928.1	73.8	111.2

Table 4.10: Periodic information update case: Comparison of NCR and CR return policies with $\overline{SL1}$ and $\overline{SL2}$ values of each three dispatching policies

Real-time vs. Periodic (CR)	Real-time	Periodic	Real-time	Periodic	Real-time	Periodic
Service Levels	FCFS policy	FCFS policy	SDF policy	SDF policy	MCPF policy	MCPF policy
Overall service level, RTH based	0.632	0.591	0.867	0.866	0.804	0.804
Overall service level, RTT based	0.626	0.586	0.855	0.855	0.795	0.795
Type 1 service level, RTH based	0.632	0.591	0.867	0.866	1.000	1.000
Type 1 service level, RTT based	0.626	0.585	0.854	0.854	1.000	1.000
Type 2 service level, RTH based	0.632	0.591	0.867	0.867	0.675	0.673
Type 2 service level, RTT based	0.627	0.586	0.856	0.856	0.646	0.644
Type 3 service level, RTH based	0.632	0.592	0.866	0.865	0.007	0.010
Type 3 service level, RTT based	0.630	0.588	0.857	0.857	0.007	0.010

Table 4.11 and Table 4.12 display the results of the increased velocity case with CR return policy. It is observed that overall $\overline{RTH}$ and $\overline{RTT}$ values does not differ too much between 25 km/h or 35 km/h, but service levels change a lot. Especially the improvement in type 2 service level by testing with 35 km/h in MCPF policy is dramatic. Some of the average response times are increased with increased velocity in SDF and MCPF (tie-breaker is SDF) because more patients are served even if these patients are far (all the nearby patients to hospitals are served so ambulances are able to serve to longer distances).

Table 4.11: Increased velocity case: Comparison of NCR and CR return policies with $\overline{RTH}$ and $\overline{RTT}$ values of each three dispatching policies

Increased velocity effect (CR)	25 km/h	35 km/h	25 km/h	35 km/h	25 km/h	35 km/h
Average RTH and RTT values	FCFS policy	FCFS policy	SDF policy	SDF policy	MCPF policy	MCPF policy
Overall average RTH (min)	2816.1	2572.5	1883.3	1926.5	2093.1	2142.7
Overall average RTT (min)	2854.8	2617.7	1943.0	1991.3	2185.5	2238.9
Type 1 average RTH (min)	2816.4	2573.0	1882.5	1925.5	1155.2	1011.9
Type 1 average RTT (min)	2861.3	2624.9	1948.3	1996.1	1298.0	1170.7
Type 2 average RTH (min)	2814.9	2571.4	1887.7	1930.7	4890.5	4564.1
Type 2 average RTT (min)	2847.1	2609.8	1942.0	1990.3	4954.6	4620.8
Type 3 average RTH (min)	2817.1	2572.3	1875.1	1919.4	37.9	418.5
Type 3 average RTT (min)	2838.6	2598.1	1913.8	1966.3	73.8	390.2

In Appendix, from Figure from 3 to Figure 8, hourly service levels of combinations of FCFS, SDF, MCPF dispatching policies with NCR, CR return policies are given. Those figures represent 5 hours and 10 hours service levels of type 1 injuries. For SDF and FCFS

Table 4.12: Increased velocity case: Comparison of NCR and CR return policies with $\overline{SL1}$ and $\overline{SL2}$ values of each three dispatching policies

Increased velocity effect (CR)	25 km/h	35 km/h	25 km/h	35 km/h	25 km/h	35 km/h
Service Levels	FCFS policy	FCFS policy	SDF policy	SDF policy	MCPF policy	MCPF policy
Overall service level, RTH based	0.632	0.806	0.867	0.940	0.804	0.883
Overall service level, RTT based	0.626	0.798	0.855	0.924	0.795	0.872
Type 1 service level, RTH based	0.632	0.806	0.867	0.940	1.000	1.000
Type 1 service level, RTT based	0.626	0.797	0.854	0.923	1.000	1.000
Type 2 service level, RTH based	0.632	0.806	0.867	0.940	0.675	0.934
Type 2 service level, RTT based	0.627	0.799	0.856	0.926	0.646	0.899
Type 3 service level, RTH based	0.632	0.806	0.866	0.940	0.007	0.023
Type 3 service level, RTT based	0.630	0.802	0.857	0.927	0.007	0.019

policy, type 2 and type 3 graphics are similar because there is no priority based on injury. Overall, these six figures indicate the success of MCPF policy for severe injuries. It is assumed that most of the patients require ambulances would be severe injury, therefore it is more logical to implement MCPF policy after the expected earthquake. However, it is important to teach triage to the rescue teams and military members. Hopefully, authorities will notice the importance of teaching triage to rescue teams so that many lives could be saved.

4.5 The effects of establishing temporary emergency hospitals after the disaster

In a post-earthquake environment in Istanbul, it is expected to be inevitable that hospital emergency services would be overwhelmed by the incoming patients. Therefore, it is essential to increase service capacity by positioning disaster environment temporary emergency hospitals (TEH) in areas with poor expected response times and service levels. We investigate system performance under different combinations of TEH locations to guide preparedness decisions.

In this section, hospital emergency service queue lengths are not taken into consideration. Moreover, social issue among neighborhoods is considered the maximum $\overline{RTH}(j)$ value of neighborhoods. We aim to decrease both $\overline{RTH}$ and decrease maximum $\overline{RTH}(j)$ of neighborhoods by opening TEHs so that response times and maximum maximum $\overline{RTh}(j)$ will be decreased and.

It was observed previously that SDF policy performs the best in terms of $\overline{RTH}$, but it is not a fair policy since some neighborhoods have very poor response times. In this section, we identified ten candidate locations based on SDF policy results to open temporary emergency hospitals. These candidates are the neighborhoods with the worst $\overline{RTH}$ values under SDF policy.

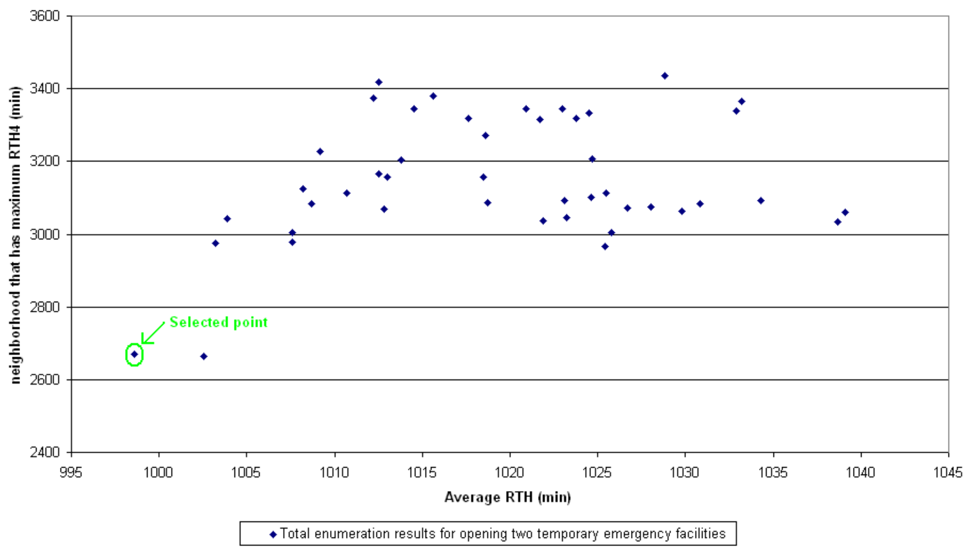

Figure 4.11: Total enumeration results of adding two TEH units

Three cases are studied in this section. These are opening two TEHs, opening four TEHs, opening six TEHs. Total enumeration is performed considering the ten candidates for each case and the results are presented in Figures 4.11, 4.12, and 4.13.

There are 465 combinations (45 for two TEHs, 210 for four TEHs, 210 for six TEHs) tested by simulation. Simulating all of the combinations takes too long; therefore, they are simulated with 10 replications instead of 50.

The results are presented for only SDF policy, since the objective of this section is to

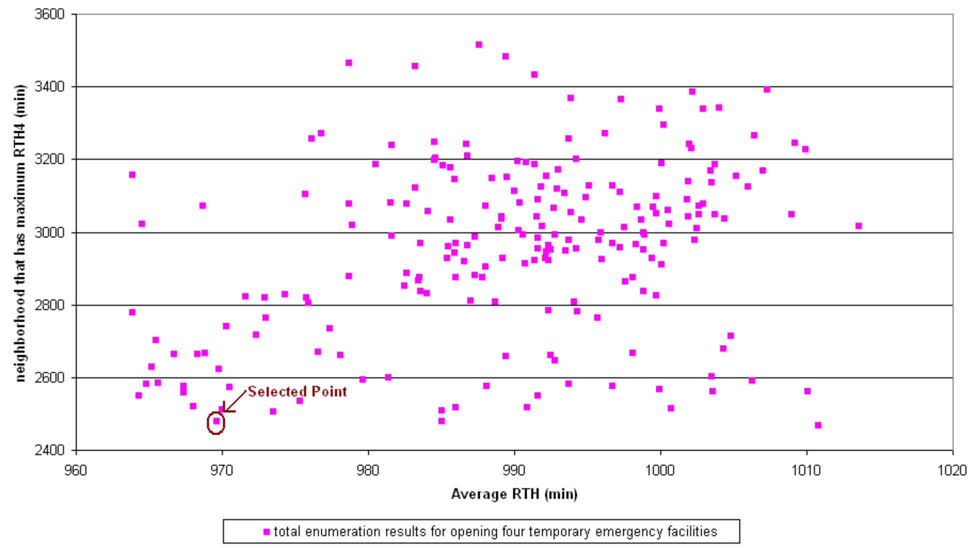

Figure 4.12: Total enumeration results of adding four TEH units

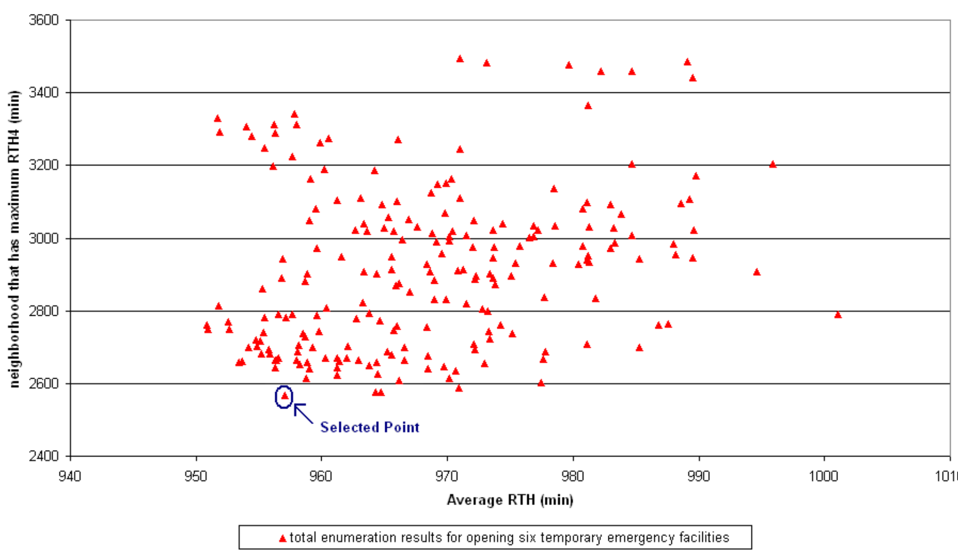

Figure 4.13: Total enumeration results of adding six TEH units

compare the effects of additional TEHs; rather than comparing policies.

Selected TEH locations for three cases are:

Two TEHs: (Neighborhood numbers 30, 82) (Figure 1)

Four TEHs: (Neighborhood numbers 30, 52, 69, 83) (Figure 1)

Six TEHs: (Neighborhood numbers 26, 30, 44, 69, 82, 85) (Figure 1)

From Table 4.13 and Table 4.14, it is observed that NCR policy $\overline{RTH}$ values are highly sensitive to additional TEH units but $\overline{RTT}$ values differ a little. However, $\overline{SL2}$ improves from 0.539 to 0.631 when 6 TEH units are opened. The effects of adding TEH units are more visible when CR policy is used as a return policy. Overall service levels are improved more than 11 percent by opening 6 TEH units and response times ($\overline{RTH}$, $\overline{RTT}$) decrease by more than 5 percent. Especially when we add 6 TEH units to the system, $\overline{SL1}$ and $\overline{SL2}$ become 0.980 and 0.964 which are very high and almost 1.000. SDF policy creates inbalance between neighborhoods and the neighborhoods which has hospitals nearby become more advantageous in receiving faster service. Therefore, standard deviation among the average response times of the neighborhoods become also important when only dealing with SDF. It is observed that, standard deviation among the neighborhoods is affected by the increasing number of TEH units in terms of RTH, but it seems uneffected in terms of RTT when SDF policy is used with NCR return policy. When CR return policy is used, standard deviation seem to be more sensitive to additional TEH units than overall average response times.

Table 4.13: The effect of different number of additional hospitals on $\overline{RTH}$ and $\overline{RTT}$ by using SDF dispatching policy with NCR or CR return policies

Additional hospitals	Without TEH	2 TEH units	4 TEH units	6 TEH units	Without TEH	2 TEH units	4 TEH units	6 TEH units
Average RTH and RTT values	SDF, NCR	SDF, NCR	SDF, NCR	SDF, NCR	SDF, CR	SDF, CR	SDF, CR	SDF, CR
Overall average RTH (min)	1101.6	949.7	852.1	748.6	1883.3	1847.8	1816.0	1781.4
Overall average RTT (min)	1836.6	1830.4	1901.0	1777.7	1943.0	1911.5	1877.7	1844.4
Std. Deviation, RTH based(min)	1186.5	1010.7	911.3	781.9	1955.6	1889.0	1843.7	1802.4
Std. Deviation, RTT based(min)	1506.9	1502.0	1505.9	1528.3	1940.9	1888.2	1830.5	1803.1

Table 4.14: The effect of different number of additional hospitals on $\overline{SL1}$ and $\overline{SL2}$ by using SDF dispatching policy with NCR or CR return policies

Additional hospitals	Without TEH	2 TEH units	4 TEH units	6 TEH units	Without TEH	2 TEH units	4 TEH units	6 TEH units
Average RTH and RTT values	SDF, NCR	SDF, NCR	SDF, NCR	SDF, NCR	SDF, CR	SDF, CR	SDF, CR	SDF, CR
Overall service level, RTH based	1.000	1.000	1.000	1.000	0.867	0.909	0.950	0.980
Overall service level, RTT based	0.539	0.590	0.601	0.631	0.855	0.896	0.935	0.964

4.6 The effects of additional ambulances

The total number of ambulances taken from [1] is 128 in the simulation model. At the beginning of the model runs, ambulances are located at the hospitals they belong to. However, during the simulation runs, ambulance locations change dynamically. Since the simulation period is long enough, we expect the effect of initial ambulance locations to phase out. In order to see the effects of adding ambulances to different locations, we added five ambulances to six neighborhoods in six distinct cases. The results are listed in Table 4.15. It is observed that the difference in $\overline{RTH}$ of adding ambulances to different locations is less than 1 percent. Therefore, we increase ambulance capacity by adding them to random locations.

Table 4.15: $\overline{RTH}$ for six distinct cases when five ambulances are added to different locations

Average RTH of location differences on additions (min)		
960.2	960.5	960.1
960.4	959.7	959.1

The results are very different from opening new TEH units. Table 4.16 indicates that $\overline{RTH}$ is very sensitive to ambulance numbers. Consequently, additions to the ambulance capacity as a pre-disaster preparedness approach provides direct benefits in reducing overall $\overline{RTH}$. Some vehicles might also be utilized instead of ambulances in case of need to improve service performance. On the other side, despite the dramatic improvement on $\overline{RTH}$, only SDF policy with NCR return policy is tested with ambulance additions. Emergency department capacity is not altered, therefore it is logical to expect that $\overline{RTT}$ values will not improve like $\overline{RTH}$.

Table 4.16: Results of increasing ambulance numbers

Additional # of ambulances	Average RTH (min)	Standard deviation (min)
5	948.52	803.04
10	871.26	754.16
15	800.31	690.07
20	740.37	653.50
25	678.92	601.51
30	629.36	572.69
40	532.09	492.10
50	448.03	423.31
60	380.45	367.42
80	279.96	275.50
100	201.23	201.59
128	131.76	129.58

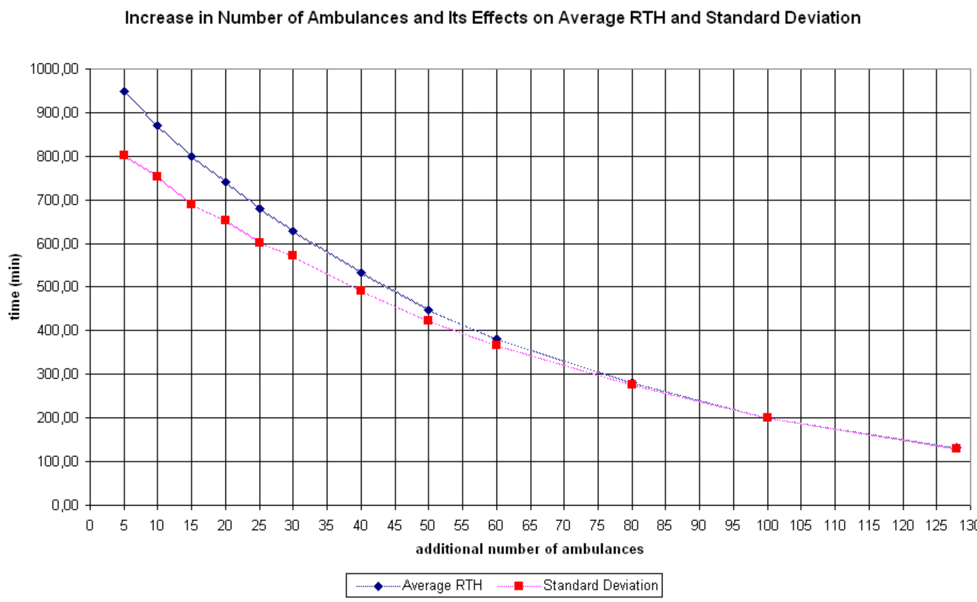

Figure 4.14: Addition of ambulances and its effects on $\overline{RTH}$ and standard deviation

Chapter 5

CONCLUSION

In this thesis, we analyzed the post-earthquake ambulance dispatching problem for the Istanbul case by a simulation model. Our objective was to assess the performance of different ambulance dispatching policies, by simulating the ambulance dispatching operations in seven districts of Istanbul and their neighborhoods. The studied seven districts are Bahçelievler, Güngören, Zeytinburnu, Bağcılar, Esenler, Bayrampaşa and Bakırköy. These areas form an almost convex region, therefore we assumed that the demand of the studied areas are only served by the supply in the studied area and the supply does not serve to the outside of the studied area. The basic assumption of the model is the centralized system assumption, that enables coordination of the decisions centrally. Other important assumptions that affect the results are the following. First, all the arrived patients must be carried by the ambulances and patients will wait for the ambulances as long as it takes without being transported with any other vehicle. Second, central system must not reject any of the ambulance requests although the ambulance requests are many and idle ambulances are low, and central system must assign an ambulance to the patient even if two or three days has passed. When the treatment times and the capacities of the ambulances are added to the simulation, some patients either can reach to hospital but can not be served in the emergency department due to long queues or can not reach to hospital at all.

The simulation model updates information on a continuous-time basis with one minute increment. A minute is a quite small time-increment to represent the events. There are more than 100,000 events in the simulation but only a total of 7200 minutes. Therefore, computational time decreases dramatically with the continuous-time approach opposed to the discrete-event approach. Although the simulation runs for 7200 minutes (5 days), the arrival process stops after 88 hours. The reason is that the survival probability of a patient under the collapsed buildings almost decreases to zero around 3 to 4 days after the earthquake. The simulation runs for five days cover and observe the service times of all patients whose services are delayed. There are four critical matrices in the simulation which are patient matrix, ambulance matrix, hospital matrix and bed matrix. The attributes in these matrices are updated as explained in Sections 3.14 and 3.15.

The exact earthquake damage can not be known in advance of the earthquake, but JICA prepared a report for the expected percentage of destruction in each neighborhood [3]. Neighborhood population data is taken from ArcGIS software, ESRI Company [2]. When we combine the population data [2] with the expected percentage of heavily damaged buildings data from the JICA Report [3], we calculate the expected number of injuries from each neighborhoods and use this number to set the patient arrival rate for each neighborhood. The arrival process is non-stationary. We keep the distribution of the interarrival times the same but the non-stationarity of arrivals is captured through batch arrivals. Therefore, the arrivals become the calls to the central call center requesting ambulances and sometimes more than one ambulance could be requested or no ambulance is requested.

The ambulance and hospital numbers and their locations are taken from a previous study of Gül [1]. The initial locations of ambulances are given in Figure 1. The travel times are estimated based on real road data [2] and isolation risk taken from JICA report [3].

Three ambulance dispatching policies and two return policies are studied. The dispatching policies are: First-called-first-served (FCFS), shortest-distance-first (SDF), and most-critical-patient-first (MCPF). In MCPF policy, we assume that rescuers can categorize the injured people into three categories severe, moderate and light injury. Studied return policies are: Non-communicating-return (NCR), which selects the closest hospital, and communicating-return (CR), which selects the hospital that can provide service in minimum expected time. These policies are explained in Section 3.10 in detail.

We use two basic performance criteria, which are response time ($\overline{RTH}$ or $\overline{RTT}$) and service level ($\overline{SL1}$ or $\overline{SL2}$).

We analyze several different cases. Real-time information case (Section 4.1) and periodic information update case (Section 4.2) give similar results and in both cases, SDF policy gives the best results for $\overline{RTH}$ but has poor performance especially in terms of fairness among neighborhoods and individuals. By fairness, we mean unequal distribution of resources among neighborhoods which are ambulances and emergency beds. On the other hand, MCPF policy arises as a good alternative when comparing fairness results but comes with a cost of increased $\overline{RTH}$ by 20 percent approximately. Average service levels are similar in SDF and MCPF for NCR return policy, and in CR return policy, average service levels of SDF policy is slightly better than MCPF policy. FCFS policy is generally used in daily life, however the results indicate that it is a very poor dispatching policy both for response times and service levels in the case of disasters.

In Section 4.3, a what-if questions is analyzed by considering increased velocity. Increasing average expected ambulance velocity by 40 percent does not make noticable differences for average response times. On the other side, average service level improvements with CR return policy shows that traffic conditions highly affect the number of patients that are served. Hence, we expect better system performance for average service levels instead of average response times if road conditions are more favorable.

In Section 4.4, In this section, two types of return policies are compared which are NCR and CR. The results indicate that the CR policy is more reliable and intensive communication between ambulance drivers and hospital coordinators is beneficial while assigning ambulances to the hospitals. SDF policy and MCPF policy gives similar results for $\overline{RTT}$ and service levels are also similar. Therefore it is more logical to adapt MCPF policy in order to save severe injuries first.

Section 4.5 analyzes the case of opening TEHs. Opening 2, 4, and 6 TEHs are considered and their locations are found by total enumeration from 10 candidate neighborhoods which display poor $\overline{RTH}(j)$ for neighborhoods under the SDF policy. The results indicate that although opening temporary emergency units decrease $\overline{RTH}$ dramatically but does not affect $\overline{RTT}$ for NCR return policy, however it affects the results for CR return policy and standard deviation between the average response times of the neighborhoods. When 6 TEH units are added, SDF policy almost serve everybody in 5 days.

Section 4.6 presents the results of adding new ambulance units to the medical system and the results indicate that $\overline{RTH}$ is highly sensitive to the balance between number of ambulances and number of patients.

Further analysis could be conducted by modeling the behavior of the patients, especially in terms of how long they are willing to wait. For example, 3 hours have passed since the patient call for an ambulance but no ambulance has been aasigned to this patient yet, then the patient may go to a hospital by other means rather than ambulances. In such a case, a new performance measure would be needed to indicate percentage of patients served. Another case to consider the fact that the centralized system may reject some of the ambulance requests due to heavy request load. Again, some patients would have to use other means of transportation rather than ambulances in such a case.

An extension of this study is to model the emergency service department of a hospital into the simulation. The results in Section 4.4 indicates that emergency treatment times and emergency capacities must be considered in the simulation.

To conclude, we have assessed the performance of the current ambulance system in Istanbul in a post-disaster environment by testing different policies with simulation. The two performance criteria, which are rescue-to-hospital time ($\overline{RTH}$) and fairness, are competing with each other and it is the decision maker's call to use which policy. Furthermore, addition of ambulances and temporary emergency service units have been analyzed. Insights obtained in this study may be useful in guiding preparedness and mitigation strategies.

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Table 1: Probability matrix for arrivals

Probabilities for requesting ambulances in a single call									
Time interval after disaster (h)		Number of ambulances that are requested by a single call							
start	end	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
0	**2**	0.5	0.3	0.2	0	0	0	0	0
2	**4**	0.3	0.2	0.2	0.2	0.1	0	0	0
4	**6**	0.1	0.2	0.2	0.2	0.2	0.1	0	0
6	**8**	0.1	0.1	0.1	0.2	0.2	0.2	0.1	0
8	**10**	0.1	0.1	0.1	0.1	0.1	0.1	0.2	0.2
10	**12**	0.1	0.1	0.1	0.1	0.1	0.2	0.2	0.1
12	**14**	0.1	0.1	0.1	0.1	0.2	0.2	0.1	0.1
14	**16**	0.1	0.1	0.1	0.2	0.2	0.1	0.1	0.1
16	**18**	0.1	0.1	0.2	0.2	0.2	0.1	0.1	0
18	**20**	0.1	0.2	0.2	0.2	0.2	0.1	0	0
20	**22**	0.1	0.2	0.3	0.2	0.1	0.1	0	0
22	**24**	0.1	0.3	0.3	0.2	0.1	0	0	0
24	**26**	0.2	0.3	0.3	0.2	0	0	0	0
26	**28**	0.2	0.4	0.3	0.1	0	0	0	0
28	**30**	0.3	0.3	0.3	0.1	0	0	0	0
30	**32**	0.3	0.4	0.3	0	0	0	0	0
32	**34**	0.4	0.3	0.3	0	0	0	0	0
34	**36**	0.5	0.3	0.2	0	0	0	0	0
36	**38**	0.5	0.4	0.1	0	0	0	0	0
38	**40**	0.6	0.3	0.1	0	0	0	0	0
40	**42**	0.6	0.4	0	0	0	0	0	0
42	**44**	0.7	0.3	0	0	0	0	0	0
44	**46**	0.8	0.2	0	0	0	0	0	0
46	**48**	0.9	0.1	0	0	0	0	0	0
48	**50**	1	0	0	0	0	0	0	0
50	**52**	0.95	0	0	0	0	0	0	0
52	**54**	0.9	0	0	0	0	0	0	0
54	**56**	0.85	0	0	0	0	0	0	0
56	**58**	0.8	0	0	0	0	0	0	0
58	**60**	0.75	0	0	0	0	0	0	0
60	**62**	0.7	0	0	0	0	0	0	0
62	**64**	0.65	0	0	0	0	0	0	0
64	**66**	0.6	0	0	0	0	0	0	0
66	**68**	0.55	0	0	0	0	0	0	0
68	**70**	0.5	0	0	0	0	0	0	0
70	**72**	0.45	0	0	0	0	0	0	0
72	**74**	0.4	0	0	0	0	0	0	0
74	**76**	0.35	0	0	0	0	0	0	0
76	**78**	0.3	0	0	0	0	0	0	0
78	**80**	0.25	0	0	0	0	0	0	0
80	**82**	0.2	0	0	0	0	0	0	0
82	**84**	0.15	0	0	0	0	0	0	0
84	**86**	0.1	0	0	0	0	0	0	0
86	**88**	0.05	0	0	0	0	0	0	0

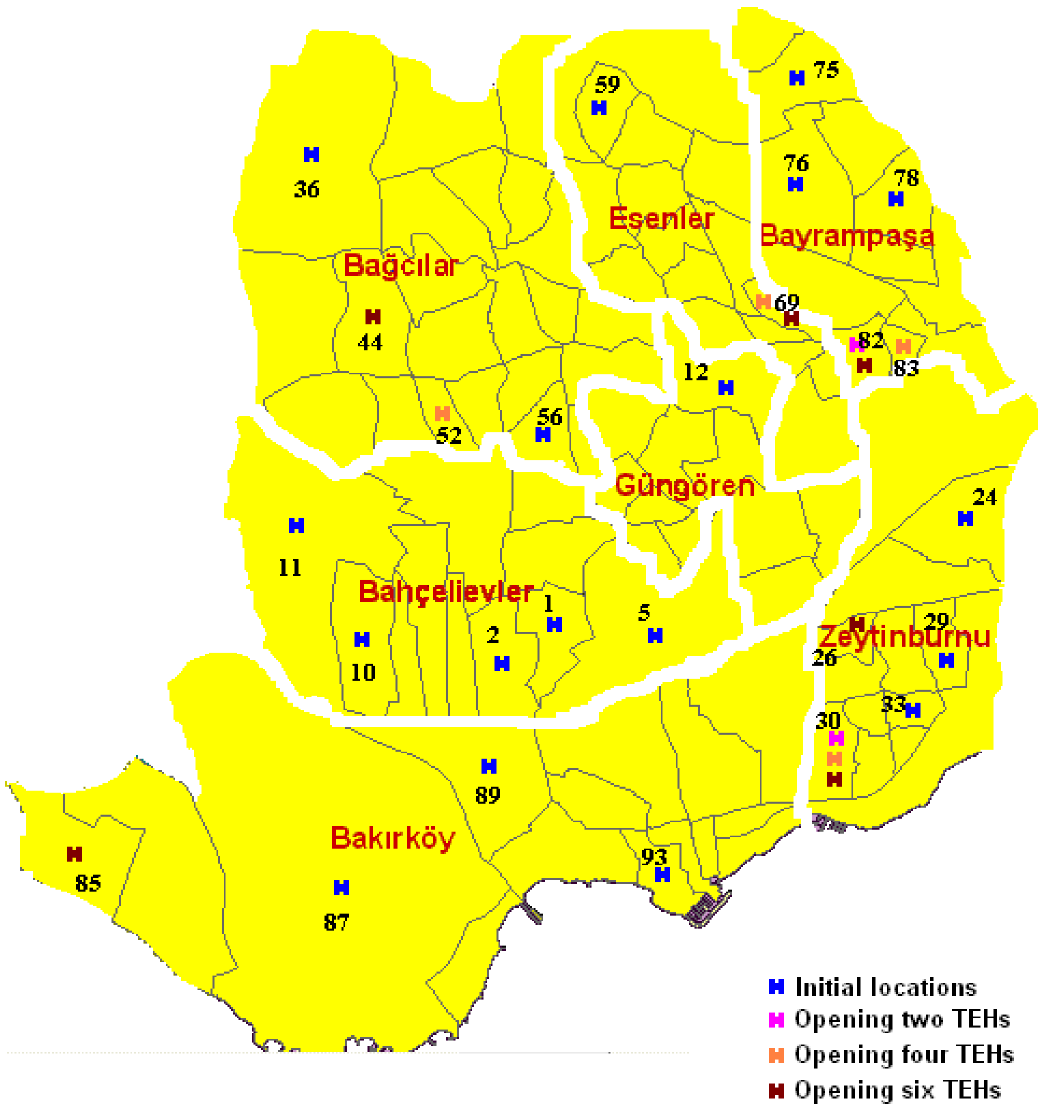

Figure 1: Initial hospital locations and TEH locations

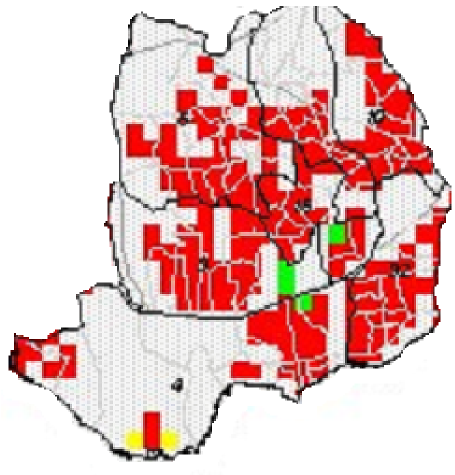

Figure 2: Isolation risks of neighborhoods [3]

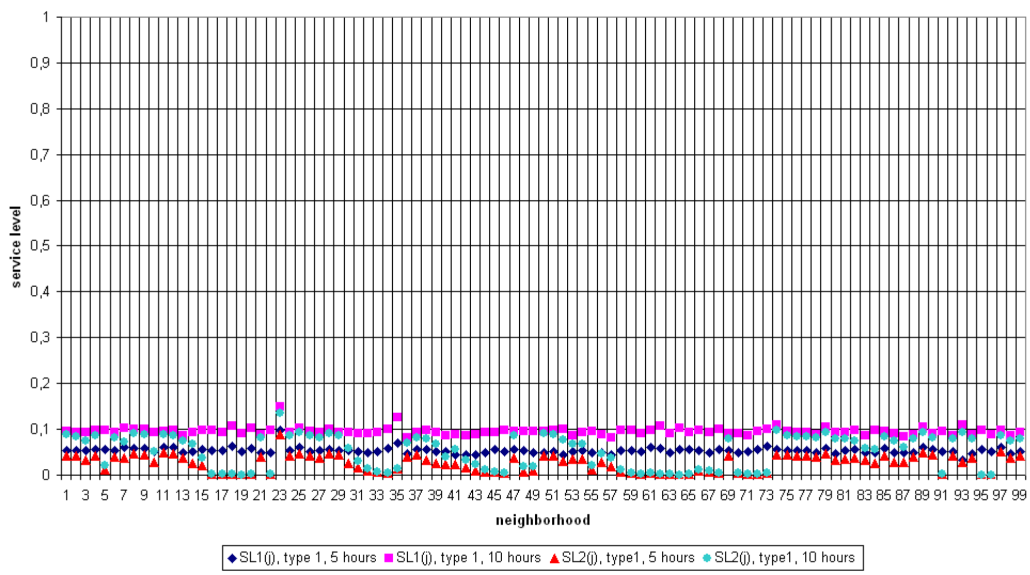

Figure 3: Comparison of $5hoursSL1$ and $5hoursSL2$ for type 1 injury, FCFS, NCR

Table 2: Travel times and coefficients with velocity: 6 km/h (not converted to 25 km/h or 35 km/h), Neighborhoods 1-50

		Hospitals																	
		coefficients of hospitals																	
		2	1,9	1,1	1,5	1,2	1,6	1,5	1,9	2	1	2	1	1,7	1,1	1,9	1,1	1	1,2
coefficients	Neighborhoods	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
2	1	5	10	16	27	39	47	64	61	55	76	31	74	94	84	84	50	32	44
1,9	2	10	5	22	21	36	53	69	66	60	74	33	79	99	91	90	42	27	40
1,9	3	14	18	18	31	35	36	63	63	60	67	19	62	83	74	73	58	41	50
1,9	4	15	7	29	14	30	57	75	72	66	71	36	80	101	95	94	38	33	45
1,1	5	16	22	5	41	53	38	50	47	44	82	31	74	90	77	76	59	39	35
2	6	20	16	34	12	21	58	83	80	73	67	33	76	97	93	95	39	42	54
1,9	7	22	14	35	6	25	64	82	79	73	75	42	85	106	101	101	32	38	51
2	8	22	25	25	38	37	33	64	67	63	62	10	56	77	71	70	65	49	57
1,5	9	26	24	33	26	23	46	74	76	73	52	18	61	81	77	83	53	51	63
1,5	10	27	21	41	5	20	67	89	86	79	69	43	86	106	103	103	28	46	58
1,2	11	39	36	53	20	5	67	94	96	92	60	40	81	103	99	104	36	62	74
1,6	12	47	53	38	67	67	5	48	60	62	68	32	42	53	40	39	93	74	71
1,7	13	36	41	33	54	51	20	55	67	64	62	14	44	64	57	56	80	62	66
2	14	33	42	28	55	56	16	45	57	55	71	22	48	66	54	54	82	62	60
1,4	15	39	48	28	62	63	13	39	51	51	77	30	51	65	51	50	84	54	61
2	16	25	32	22	45	46	23	53	57	54	68	15	54	72	61	60	71	53	54
2	17	26	35	19	48	49	26	48	52	50	73	21	57	75	63	63	74	54	52
2	18	21	30	12	45	48	30	50	50	46	76	24	64	82	69	68	68	48	45
1,6	19	25	35	16	49	51	25	45	48	45	78	26	61	76	63	63	72	52	48
1,4	20	39	46	26	63	65	22	34	41	41	86	37	62	71	56	54	82	62	59
1,5	21	49	55	34	73	74	29	22	34	40	93	45	68	62	47	45	90	68	62
1,6	22	39	45	24	63	68	32	33	33	31	95	43	71	76	61	59	77	56	50
1	23	63	71	52	86	88	35	17	29	40	96	59	66	56	42	35	104	82	76
1,5	24	64	69	50	89	94	48	5	20	32	109	65	80	71	56	50	101	80	73
1,6	25	54	59	40	78	89	52	15	12	20	114	64	85	77	62	56	10	69	60
2	26	47	52	33	72	82	49	27	16	16	110	57	88	87	73	66	84	63	47
2	27	49	54	36	73	86	53	31	16	12	114	60	92	90	76	71	84	62	43
2	28	56	61	42	81	91	59	23	7	11	119	66	95	86	71	65	92	70	52
1,9	29	61	66	47	86	96	60	20	5	13	122	71	93	84	69	63	98	76	58
2	30	49	54	38	73	86	57	41	25	15	115	62	94	98	83	80	83	58	34
2	31	49	54	39	74	87	57	33	17	8	116	63	94	94	80	73	84	62	42
2	32	54	59	43	78	91	62	40	23	12	120	67	99	101	87	80	89	61	37
2	33	55	60	44	79	92	62	32	13	5	121	68	100	94	80	74	89	68	48
2	34	56	61	45	80	93	64	15	17	8	122	69	101	98	83	77	90	67	42
1,2	35	58	63	47	83	96	65	31	13	7	125	71	103	94	79	73	93	70	46
1	36	76	74	82	69	60	68	109	122	121	5	54	45	75	71	84	92	101	113
1,2	37	75	75	76	75	67	55	94	107	112	23	47	28	58	55	68	99	101	108
1	38	77	79	78	86	79	51	89	102	109	40	48	11	47	44	56	111	104	110
1,6	39	61	61	67	62	54	49	91	103	103	21	37	34	62	58	71	86	87	99
1,3	40	63	63	64	70	62	47	88	101	100	25	35	25	55	51	64	94	89	97
1,4	41	62	63	62	70	64	41	82	94	97	33	32	21	48	44	57	96	88	94
1,6	42	55	59	56	66	61	34	75	88	89	38	28	23	47	43	56	93	82	88
1,7	43	64	63	70	50	37	64	106	114	110	27	45	59	86	82	95	69	89	102
1,9	44	53	51	59	45	37	52	95	102	99	27	34	50	75	71	84	69	78	91
1,8	45	54	53	59	54	46	44	86	99	97	26	29	39	64	60	73	78	79	91
1,6	46	46	46	52	49	41	42	84	92	89	35	22	45	70	66	77	73	72	84
1,6	47	47	47	47	54	50	32	75	86	83	40	17	35	57	53	66	81	73	79
1,4	48	46	50	46	58	55	29	70	83	82	43	19	31	51	47	60	85	73	78
1,6	49	48	53	46	61	58	19	63	76	74	51	22	31	50	46	54	88	75	78
1,1	50	51	48	57	32	20	58	97	100	96	41	35	63	88	84	94	56	74	86

Table 3: Travel times and coefficients with velocity: 6 km/h (not converted to 25 km/h or 35 km/h), Neighborhoods 51-99

		Hospitals																	
		coefficients of hospitals																	
		2	1,9	1,1	1,5	1,2	1,6	1,5	1,9	2	1	2	1	1,7	1,1	1,9	1,1	1	1,2
coefficients	Neighborhoods	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1,8	51	41	39	47	33	26	49	87	90	86	40	25	58	81	77	85	57	66	78
2	52	36	34	42	37	32	44	79	85	82	42	17	54	76	72	80	63	61	74
2	53	36	35	41	41	36	40	76	82	79	44	13	49	71	67	75	68	61	73
1,9	54	37	38	39	46	43	32	73	79	76	47	8	43	64	60	67	72	63	71
1,3	55	42	47	40	59	56	20	58	70	69	56	19	38	57	53	56	86	69	72
2	56	31	33	31	43	40	32	65	71	68	54	5	47	67	64	68	70	57	63
2	57	28	33	27	47	45	26	58	64	61	61	8	49	68	63	62	73	55	60
1	58	83	88	83	95	92	48	85	97	107	57	56	13	40	37	50	123	110	115
1	59	74	79	74	86	81	42	80	93	100	45	47	5	37	33	46	113	101	107
1	60	73	78	73	85	82	36	73	86	96	50	46	9	29	25	38	112	100	105
1,2	61	70	77	64	85	82	27	63	76	85	57	47	22	27	22	35	112	98	97
1,3	62	59	64	59	71	68	31	71	84	89	42	32	16	39	35	48	98	86	92
1,1	63	67	72	66	79	76	31	67	80	90	47	40	15	33	29	42	106	94	98
2	64	54	59	52	67	64	21	62	75	78	50	28	25	43	39	52	94	81	85
1,9	65	61	68	56	76	73	21	59	72	81	53	37	23	37	33	45	102	89	79
1,9	66	62	69	56	81	78	19	54	67	77	62	42	31	38	33	44	107	90	88
2	67	57	63	51	74	71	14	54	66	75	59	35	30	41	36	44	101	85	83
2	68	50	57	44	70	71	8	49	62	68	63	35	36	47	39	39	96	78	77
1,8	69	67	74	60	87	88	23	45	57	67	72	52	41	36	31	33	113	95	92
2	70	56	63	49	76	77	13	41	54	64	69	41	39	45	31	31	103	84	81
2	71	57	63	49	76	77	12	37	49	59	74	41	44	44	30	29	103	85	81
2	72	63	70	52	83	84	18	32	45	55	79	47	50	44	29	28	108	88	81
1,3	73	58	66	47	81	83	21	27	40	50	83	50	54	51	36	36	103	82	76
1	74	103	108	99	115	112	62	82	95	105	75	76	45	13	26	36	143	130	131
1,7	75	94	99	90	106	103	53	71	84	94	75	67	37	5	17	25	133	121	121
1,1	76	84	91	77	103	99	40	56	69	80	71	64	33	17	5	15	129	112	107
1,9	77	88	94	80	107	104	43	60	73	83	76	68	38	16	12	12	134	116	110
1,9	78	84	90	76	103	104	39	50	63	74	84	58	46	25	15	5	130	111	105
2	79	77	84	70	97	98	33	43	55	66	88	62	50	31	17	9	124	105	98
1,7	80	81	89	70	102	103	37	39	52	62	91	66	56	38	24	15	126	105	98
1,7	81	68	75	60	88	89	23	43	56	66	81	52	49	35	21	24	114	96	92
2	82	66	72	55	86	87	21	31	44	54	82	50	52	42	28	22	111	90	84
2	83	70	78	59	91	92	27	30	42	53	87	56	57	44	30	23	115	94	87
1,5	84	74	82	63	97	99	34	30	44	55	95	64	65	48	34	25	118	97	91
1,4	85	91	83	100	71	58	123	143	140	131	112	95	138	159	155	160	62	93	95
1,1	86	88	80	97	69	57	122	139	136	127	110	94	137	158	154	159	58	87	85
1,1	87	50	41	58	28	36	93	101	98	89	92	69	112	133	129	129	5	52	64
1	88	54	50	61	66	75	96	102	90	80	123	79	123	144	135	133	40	40	38
1	89	32	27	39	46	62	74	80	76	68	101	57	101	121	112	111	52	5	33
1,6	90	37	32	43	51	67	79	81	67	57	106	62	106	127	115	113	56	23	15
1,9	91	24	29	19	48	62	56	60	53	44	96	46	89	108	93	91	57	33	19
1,1	92	31	26	33	44	60	69	71	59	51	99	56	100	119	105	102	51	19	18
1,2	93	42	40	35	58	74	71	73	58	48	113	63	107	121	107	105	65	33	5
2	94	40	40	32	59	75	68	66	51	41	111	61	104	116	101	99	65	33	8
2	95	31	36	23	55	68	56	55	41	33	102	51	92	104	89	87	63	39	23
1,4	96	34	39	24	59	72	47	44	30	21	105	52	84	93	79	76	69	47	32
2	97	41	43	33	61	77	68	64	48	38	112	62	105	114	100	98	68	36	11
1,8	98	43	47	36	65	81	62	58	43	33	115	64	99	108	93	91	71	40	18
1,7	99	46	49	39	68	84	64	59	42	32	118	67	101	110	96	94	74	42	17

Table 4: Patient arrival rates of neighborhoods

Estimated Mean Arrival Rates of Poisson Distribution					
Neighborhood 1-33		Neighborhood 34-66		Neighborhood 67-99	
1	0.091	34	0.034	67	0.022
2	0.079	35	0.003	68	0.03
3	0.093	36	0.008	69	0.005
4	0.064	37	0.022	70	0.017
5	0.075	38	0.016	71	0.022
6	0.107	39	0.035	72	0.02
7	0.034	40	0.016	73	0.004
8	0.024	41	0.012	74	0.006
9	0.035	42	0.02	75	0.031
10	0.04	43	0.032	76	0.013
11	0.036	44	0.027	77	0.029
12	0.047	45	0.022	78	0.046
13	0.035	46	0.027	79	0.022
14	0.067	47	0.018	80	0.023
15	0.019	48	0.012	81	0.035
16	0.023	49	0.024	82	0.019
17	0.031	50	0.008	83	0.022
18	0.031	51	0.015	84	0.021
19	0.025	52	0.012	85	0.011
20	0.013	53	0.017	86	0.034
21	0.03	54	0.032	87	0.016
22	0.031	55	0.016	88	0.013
23	0.002	56	0.052	89	0.03
24	0.029	57	0.015	90	0.015
25	0.03	58	0.017	91	0.043
26	0.037	59	0.016	92	0.01
27	0.056	60	0.011	93	0.002
28	0.036	61	0.007	94	0.007
29	0.05	62	0.015	95	0.071
30	0.048	63	0.009	96	0.031
31	0.028	64	0.029	97	0.007
32	0.034	65	0.024	98	0.009
33	0.027	66	0.02	99	0.011

Table 5: Hospital and ambulance data set [1]

No:	Hospital Name	Emergency Beds	Ambulances
1	P.H	10	3
2	Ozel John.F Kennedy H *	5	3
	O.Medical Park Bahcelievler H *	5	3
3	O.Medicana Hospitals Bahcelievler H	5	3
4	P.H	8	3
5	Bagcilar EAH ****	15	6
6	Bayrampasa Sagmalcilar DH **	6	5
7	Vakif Gureba EAH	10	5
8	I.U. Cerrahpasa Tip Fak.H	30	7
9	O.Memorial H	5	5
10	P.H	4	16
11	P.H	8	9
12	P.H	2	6
13	P.H	10	8
14	O.Avrupa Safak H	8	8
15	Eyup DH ***	16	5
16	O.Istanbul International H	5	9
17	Bakirkoy Dr. Sadi Konuk EAH	25	13
18	O.Acibadem Bakirkoy H	8	8

* These two hospitals are in the same neighborhood, therefore they are treated as one hospital together

** This hospital is in Bayrampaşa, but it is shown inside one of the neighborhoods in Güngören near Bayrampaşa border, therefore it is assumed that this hospital is in Güngören

*** This hospital is in Eyüp, and Eyüp is not a studied district. However, this hospital is very close to the border of Bayrampaşa, therefore it is added to the studied medical system.

**** This hospital is shown in the borders of Bahçelievler, therefore it is assumed in Bahçelievler

P.H means private hospital

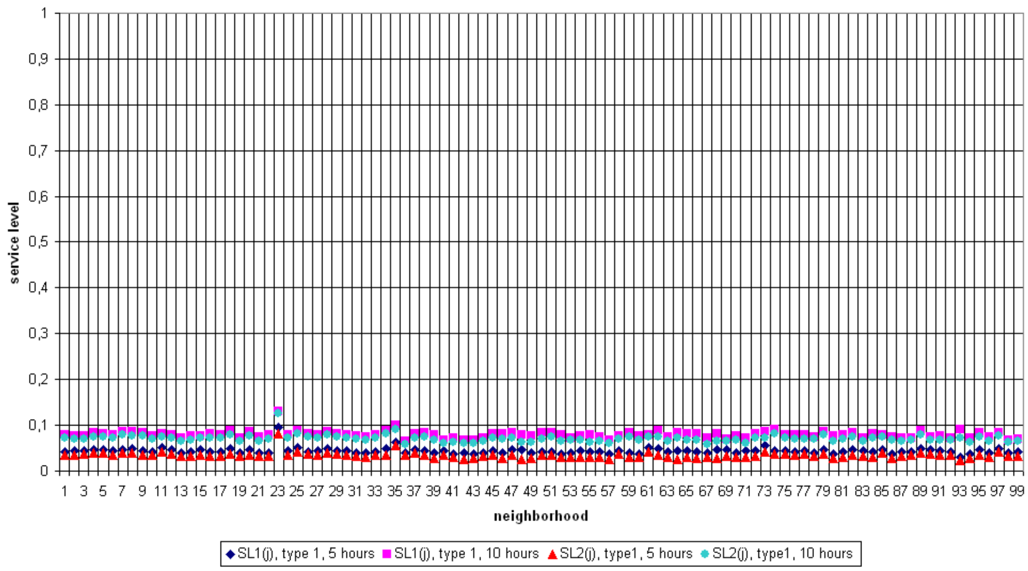

Figure 4: Comparison of $5hoursSL1$ and $5hoursSL2$ for type 1 injury, FCFS, CR

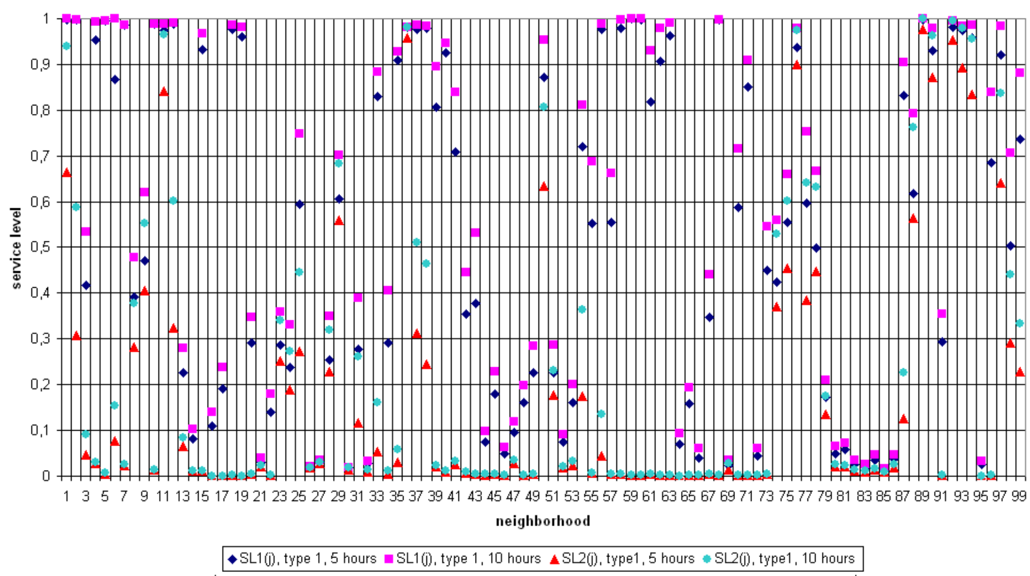

Figure 5: Comparison of $5hoursSL1$ and $5hoursSL2$ for type 1 injury, SDF, NCR

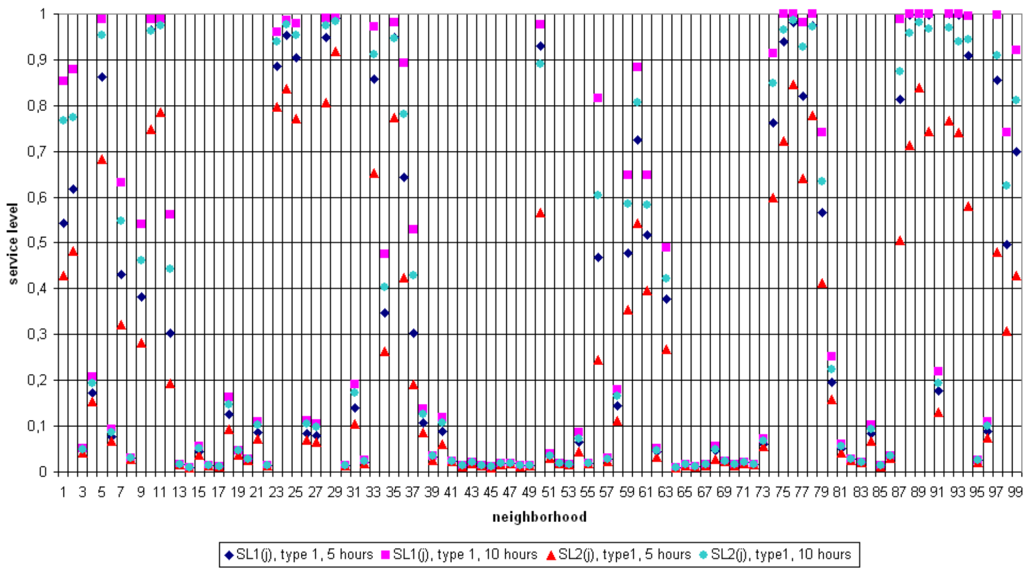

Figure 6: Comparison of $5hoursSL1$ and $5hoursSL2$ for type 1 injury, SDF, CR

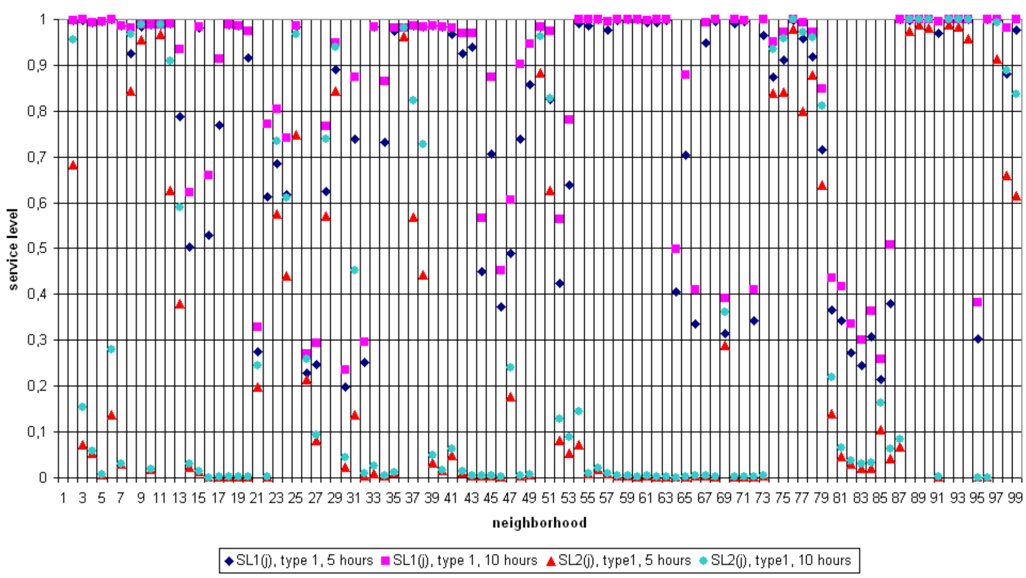

Figure 7: Comparison of $5hoursSL1$ and $5hoursSL2$ for type 1 injury, MCPF, NCR

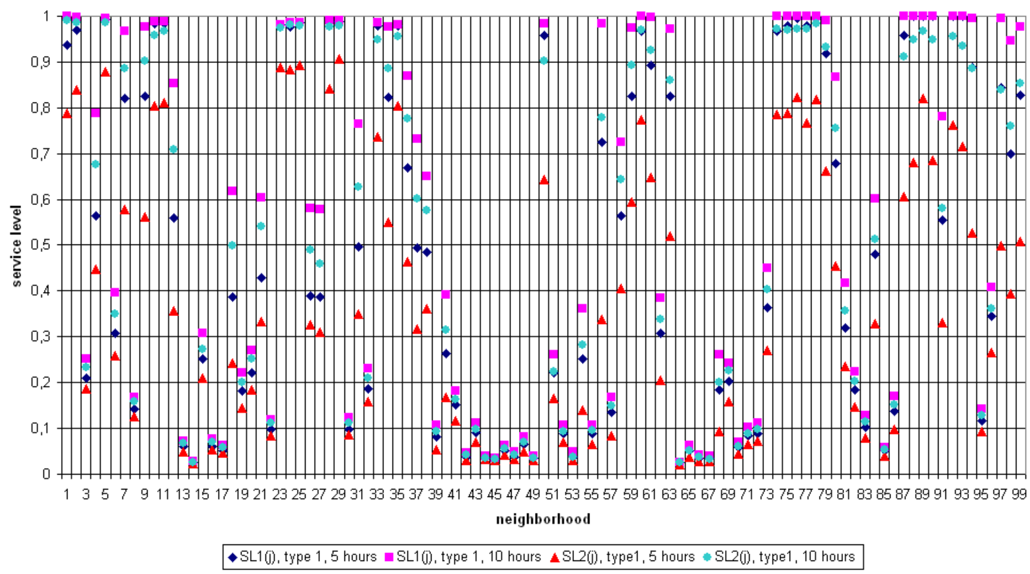

Figure 8: Comparison of $5hoursSL1$ and $5hoursSL2$ for type 1 injury, MCPF, CR

VITA

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