AN INTEGRATED OPTIMIZATION AND SIMULATION APPROACH FOR THE AMBULANCE LOCATION PROBLEM

A THESIS SUBMITTED TO
THE GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES
OF
MIDDLE EAST TECHNICAL UNIVERSITY

BY

MEDİNE ŞAHİN MACİT

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR
THE DEGREE OF MASTER OF SCIENCE
IN
INDUSTRIAL ENGINEERING

DECEMBER 2015

Approval of the thesis:

AN INTEGRATED OPTIMIZATION AND SIMULATION APPROACH FOR THE AMBULANCE LOCATION PROBLEM

submitted by **MEDİNE ŞAHİN MACİT** in partial fulfillment of the requirements for the degree of **Master of Science in Industrial Engineering Department, Middle East Technical University** by,

Prof. Dr. Gülbin Dural Ünver ______________________
Dean, Graduate School of **Natural and Applied Sciences**

Prof. Dr. Murat Köksalan ______________________
Head of Department, **Industrial Engineering**

Accoc. Prof. Dr. Sedef Meral ______________________
Supervisor, **Industrial Engineering Dept., METU**

Examining Committee Members:

Prof. Dr. Nur Evin Özdemirel ______________________
Industrial Engineering Dept., METU

Accoc. Prof. Dr. Sedef Meral ______________________
Industrial Engineering Dept., METU

Assist. Prof. Dr. Sakine Batun ______________________
Industrial Engineering Dept., METU

Assist. Prof. Dr. Melih Çelik ______________________
Industrial Engineering Dept., METU

Assist. Prof. Dr. Diclehan Tezcaner Öztürk ______________________
Industrial Engineering Dept., TED University

Date: 07.12.2015

I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

Name, Last name : MEDİNE ŞAHİN MACİT

Signature :

ABSTRACT

AN INTEGRATED OPTIMIZATION AND SIMULATION APPROACH FOR THE AMBULANCE LOCATION PROBLEM

Şahin Macit, Medine
M.S., Department of Industrial Engineering
Supervisor: Assoc. Prof. Dr. Sedef Meral

December 2015, 159 Pages

Management of smooth-functioning Emergency Medical Services (EMS) along with efficient and effective utilization of ambulances which are an essential part of this service is of vital importance. Selecting the suitable location of ambulance stations and the allocation of ambulances to their corresponding stations are important decisions which directly affect the quality of response to an emergency case. In this study, an integrated optimization and simulation approach is proposed so as to determine the size of the ambulance fleet, the location of stations and the allocation of the ambulances to these stations. This approach includes a covering model, namely Gradual Maximum Expected Covering Location Problem (G-MEXCLP), and a generic EMS system simulation model used in succession in the search for the best solution in an iterative manner. We use several test problems in the literature to validate the G-MEXCLP model. We then test the integrated approach using the data of the city of Adana, and demonstrate the advantages of the approach by comparing the results obtained to the current ambulance location plan for the City of Adana.

Keywords: Emergency Medical Service, Ambulance, Location, Simulation, Maximum Expected Covering Location

ÖZ

AMBULANS YERLEŞİMİ İÇİN BİR BİRLEŞİK OPTİMİZASYON VE BENZETİM YAKLAŞIMI

Şahin Macit, Medine
Yüksek Lisans, Endüstri Mühendisliği Bölümü
Tez Yöneticisi : Doç. Dr. Sedef Meral
Aralık 2015, 159 Sayfa

Acil servis hizmetlerinin aksamadan yürütülebilmesi ve bu hizmetin çok önemli bir parçası olan ambulansların verimli ve etkili bir şekilde kullanılabilmesi hayati bir öneme sahiptir. Ambulansların yerleştirileceği uygun istasyonları seçmek ve eldeki ambulansların bu istasyonlara nasıl dağıtılacağını belirlemek, acil bir duruma cevap verme kalitesini doğrudan etkileyen önemli kararlardır. Bu çalışmada; ambulans filosunun büyüklüğünü, istasyonların konumlarını ve ambulansların istasyonlara atanmasını belirlemek amacıyla, yeni bir birleşik optimizasyon ve benzetim yaklaşımı önerilir. Bu yaklaşım; en iyi çözümü elde etmek için, yinelemeli bir biçimde ardarda kullanılan, kademeli maksimum tahmini kapsama yerleşim problemi adıyla yeni bir kapsama modeli (G-MEXCLP) ve kapsamlı bir acil servis sistemi benzetim modeli içerir. Bu kapsama modelinin doğrulanması için literatürde yer alan bir çok test problemi kullanılır. Daha sonra önerilen bu birleşik yaklaşım Adana Şehrine ait veri ile test edilir ve elde edilen sonuçlar Adana şehrinin mevcut ambulans yerleşimi ile karşılaştırarak yaklaşımın avantajları gösterilir.

Anahtar Kelimeler: Acil Servis Sistemi, Ambulans, Yerleşim, Benzetim, Maksimum Tahmini Kapsama Yerleşimi

To my family

ACKNOWLEDGEMENTS

First of all, I would like to thank my supervisor Assoc. Prof. Dr. Sedef Meral for her kind guidance, encouragement and advice throughout the study. I would like to express my sincere appreciation for her motivation and friendly support in completing the research.

I also appreciate the support of my company, ROKETSAN A.Ş., my colleagues especially my managers for their patience.

I express my gratitude to my father Şahin Şahin, my mother Sema Şahin, my sisters Fatime Şahin and Medihanur Şahin and to all other family members for their love, moral support, and encouragement throughout my whole life.

Finally, I would like to thank my husband Burak Macit who is always with me whenever I need. This study would have never been completed without his support and motivation. I always feel his everlasting love and endless encouragement.

TABLE OF CONTENTS

LIST OF TABLES

TABLES

LIST OF FIGURES

FIGURES

CHAPTER 1

INTRODUCTION

When an emergency medical incident occurs, Emergency Medical Service (EMS) is the public service that provides necessary medical care at the place of the incident and if needed, transports the patients suffering from the incident to an appropriate medical center. The most important goal of this service is to reach the scene of the emergency incident quickly, to save lives, and to prevent irreversible effects of the injuries by applying some acute medical treatment. The vital nature of EMS systems obligates strategic planning in order to overcome the difficulty of not having an infinite number of ambulances to respond to each and every incident or patient with a response time of almost zero.

Ambulances and their crew are at the heart of the EMS system as they are the core resources of this system. While managing these resources, it is very important to consider the interest of all the population and make strategic plans accordingly. There are several factors affecting the course of these plans, namely the locations of the facilities where the ambulances are sited, how demand for this service is categorized and rules to allocate the ambulances to the chosen facilities, given the fact that a spatially distributed demand exists for EMS.

The problem may seem to be an ordinary facility location problem; however, the ambulance location problem must be addressed with special attention, since one of the objectives is to handle the affairs of human life. Hence, using merely “minimizing cost” approach is not sufficient; the focus should be on reaching a greater percent of the population with a high service quality. Especially, minimizing the response time to an emergency call, in other words, time between receiving a call and reaching the scene of the call, is of crucial importance.

For the reasons stated above, the topic of EMS has attracted many researchers, and hence a large number of studies has been conducted that try to improve and enhance EMS systems. The studies mostly provide decision support systems and methodologies for the authorities in EMS, i.e., decision makers. The most important problem that they address is the efficient usage of EMS resources, especially ambulances and improving the quality of EMS. They aim to achieve substantial coverage, in other words, they aim to reach a portion of the emergency calls received by an EMS system within some predefined standards, by means of selecting better options among a pool of potential stations for the ambulances to reside, which is called as the ambulance location problem. For this purpose, mathematical models that are solved usually with heuristic approaches, both simulations and exact methods have been developed (Li et al., 2010).

This problem has been investigated for over 40 years. Earlier static mathematical models fail to reflect the fact that the coverage is not as planned when the ambulance assumed to cover a demand point is busy elsewhere (Brotcorne et al., 2003). The latter models even provided “multiple coverage” (coverage by multiple ambulances or stations) of demand points to solve this problem; still they are not able to consider real busy fractions of ambulances. Recently developed dynamic models using repeated relocations can address this problem better than the static models. On the other hand, they have greater complexity with respect to the static models, require excessive processing power, and demand new optimization strategies.

In this study, a new approach to the problem is proposed, which is mainly an integrated use of an optimization model and a simulation model in succession iteratively for the ambulance location and allocation to the stations. In this study, the mathematical model is a probabilistic one, and the simulation model is a generic model.

The mathematical model proposed is an extension to the Maximum Expected Covering Location Problem (MEXCLP) which is named as G-MEXCLP. G-MEXCLP introduces gradual coverage option to MEXCLP, providing options for the more precise definition of goals. The gradual coverage option in this context means providing different time standards for each additional coverage of a call point (Daskin et al., 1988).

The simulation model, on the other hand, is a generic simulation model that is built to test the behavior and analyze the results of the mathematical model, focusing on some critical performance measures evaluation. The purpose to build such a simulation model is to counterbalance the inability of the mathematical model in reflecting real world problems with probabilistic time distributions of events and overestimation of coverage, etc.

In this study, the integrated approach, using both a mathematical model and a simulation model, combines the optimal exact solution of the mathematical model with the reliability provided by the simulation environment. The mathematical model helps finding the initial locations of the ambulances using some initial parameter settings. Then, ambulance locations are used as input to the simulation model to evaluate the performance of the system in a stochastic environment in which the arrival time of calls, travel times, service times are all random variables. If the performance of the system is not found to be satisfactory, the mathematical model is reconstructed by the updated parameters, and iteratively some initially assigned parameters in the mathematical model such as the busy fraction converge to a better approximation obtained from the simulation model to better overcome the pitfalls of other similar location covering models.

The organization of remainder of this work is as follows: literature review of the related studies is given in Chapter 2. Starting with earlier and simpler model formulations, the studies are categorized according to their approaches to the EMS problems. They are presented with their methodologies, mathematical models along with their extensions. In Chapter 3, operation of the EMS system is described, and the problem is defined with a broader perspective. Subjects emerging when dealing with EMS systems are investigated in detail. In Chapter 4, G-MEXCLP model that we develop to locate ambulances at suitable sites is presented with its mathematical formulation and validations. In Chapter 5, a generic simulation model is described in detail, and verification and validation results obtained with suitable techniques are discussed. In Chapter 6, our solution approach is presented, which is composed of the iterations between the mathematical model and the simulation model. In Chapter 7, our solution approach is tested with the data from the city of Adana, and the results obtained at each iteration with the analysis of the simulation outputs are presented. Finally, Chapter 8 concludes with the discussions on the proposed approach, and suggests some issues for future work.

CHAPTER 2

LITERATURE REVIEW

During the past decades, Emergency Medical Service (EMS) facility location problem has been widely investigated in the academic literature. Therefore, there are many survey studies about this topic. Before we review the literature in more detail, it seems appropriate to explain these review papers.

Marianov and ReVelle (1995), make an overview about models related to the location of emergency services. They consider all types of emergency services in addition to emergency medical services. Brotcorne et al. (2003), on the other hand, present ambulance location and relocation models since 1970s by categorizing them into two classes as deterministic and stochastic models. Li et al. (2011) review covering models for emergency medical services location and planning, and optimization techniques as well to solve these models for the past few decades. Another study is conducted by Başar et al. (2012) in which they present a taxonomy for Emergency Service Station location problem by systematically classifying models in terms of objective function, constraints, model assumptions, modeling, and solution techniques. This study is valuable in providing some statistical information about the model characteristics in the literature such as the most frequently used constraint and objective function types in these models.

We review the literature based on the major covering models and their extensions by ordering them from the basic to the complex ones.

2.1. Location Set Covering Problems (LSCP)

One of the first studies about Emergency Medical Service (EMS) facility location problem is conducted by Toregas et al. (1971). Location Set Covering Problem (LSCP) is introduced for the first time which minimizes the total number of facilities activated by providing at least one facility for each demand point to be covered within a predefined distance standard. Mathematical formulation of the model is stated as follows:

Minimize $\sum_{j\epsilon W} x_j$

Subject to $\sum_{j\epsilon W_i} x_j \geq 1$, $i \epsilon V$

$x_j \epsilon \{0,1\}$, $j \epsilon W$

where:

$$x_j = \begin{cases} 0 \text{ , if an ambulance is not located at facility } j \\ 1 \text{ , if an ambulance is located at facility } j \end{cases}$$

V : the set of demand points

W : the set of potential facilities

W_i : the set of the facilities covering the demand point *i* within a predefined distance.

The objective of this model is to find the minimum number of ambulances covering all demand points in a required distance. However, the required number of ambulances could be high, since there is not any constraint on the number of ambulances. Thus, one of the main assumptions of this model is that the model allows for a total number of ambulances that is to be located as many as the number of potential facilities. Furthermore, according to this model, the facility covering its assigned demand points can respond to all emergency calls received within its service distance. However, if the ambulance is busy when another call is received, all demand points cannot be covered. Therefore, one main drawback of the LSCP is that there may be missing call that cannot be handled.

Aly and White (1978) extend this model by using probability distribution for travel times, and continuous region for the location of emergency call instead of using discrete points, so they formulate the probabilistic version of the LSCP model.

Daskin and Stern (1981) extend the missing call assumption of LSCP by first introducing the multiple coverage idea. They consider inter-district responses and upgrade LSCP model to the hierarchical set covering problem, minimizing the number of vehicles deployed while also maximizing the multiple coverage.

ReVelle and Hogan (1989b) propose a probabilistic version of the LSCP Model by minimizing the maximum response time of p ambulances with reliability level, α. In this model, response probability of an ambulance to a demand point in its coverage area is estimated by considering the deviation of the response times.

The assumptions of the LSCP model, which are the unlimited ambulance usage, and shortage of ambulances, are studied by Ball and Lin (1993). They add a constraint to guarantee that the probability of failure to respond to a call is limited by a constant value, and set an upper bound on the number of ambulances that can be located.

Marianov and Serra (2001) propose the hierarchical queuing location set covering problem (HiQ-LSCP) to minimize the number of ambulances to cover all demand.

Marianov and Serra (2002) also propose an extension of the LSCP model with a probabilistic and queuing method called the Probabilistic Location Allocation Set Covering (PLASC) Model. This model locates the minimum number of ambulance stations and allocates the demand points to these ambulance stations so as to ensure that every user will be allocated to a center within a standard time or distance, and that every user will wait in a queue with no more than b other people, with a probability of at least α.

Berman et al. (2010) develop the Cooperative Location Set Covering Model (CLSCP) as an extension of LSCP by adding a threshold value for demand coverage. They relax the assumption that only one facility determines whether a demand point is covered or not. They propose a coverage mechanism in which each facility at site j releases a "signal" that declines over distance according to a function. A demand point, i, receives signals from all facilities and is covered only if the "signal" exceeds a threshold value. This model allows for the coverage to be determined by several facilities in the customer's neighborhood.

LSCP and its extensions discussed above are listed in Table 2.1.

Table 2.1. LSCP Model and Extensions

Authors	Year	Model	Authenticity
Toregas et al.	1971	LSCP	Minimizing total number of facilities
Aly and White	1978	Probabilistic Version of LSCP	Continuous demand region
Daskin and Stern	1981	Hierarchical Version of LSCP	Multiple coverage
ReVelle and Hogan	1989b	Probabilistic Version of LSCP	α reliability level coverage
Ball and Lin	1993	Modified LSCM (Rel-P)	Upper bound for uncovered demand
Marianov and Serra	2001	Hierarchical Queuing Location Set Covering Problem (HiQ-LSCP)	Probabilistic approach by queuing theory
Marianov and Serra	2002	Probabilistic Location Allocation Set Covering Model (PLASC)	Waiting in a queue with no more than b other people, with a probability of at least α
Berman et al.	2010	Cooperative Location Set Covering Model (CLSCP)	Threshold value for demand coverage

2.2. Maximal Covering Location Problems (MCLP)

Another initial model on the EMS facility location problem is the Maximal Covering Location Problem (MCLP) introduced by Church and ReVelle (1974). This model aims to cover as many demand points as possible within the desired distance. Unlike

LSCP, the number of ambulances is not unlimited, so the model provides maximum coverage by using P ambulances. Mathematical description of the model is presented below.

Maximize $\sum_{i \epsilon V} d_i y_i$

Subject to $\sum_{j \epsilon W_i} x_j \geq y_i$, $i \epsilon V$

$\sum_{j \epsilon W} x_j = P$

$x_j, y_i \epsilon \{0,1\}$, $j \epsilon W, i \epsilon V$

where:

$$y_i = \begin{cases} 0, \text{if a demand point i is not covered at least once} \\ 1, \text{if a demand point i is covered} \end{cases}$$

d_i= population to be served at demand point i

P = number of facilities to be located

W_i : the set of the facilities covering the demand point i within a predefined distance

MCLP model is more realistic than LSCP model, since it makes use of the population as a weight for each demand point, and aims to maximize the coverage of the high population points. Still, the population is not sufficient to be used as a weight, because there are other important factors such as age, season, and likelihood of emergency incidence occurrence that affect the emergency call frequency. Nevertheless, the number of ambulances is limited in the model, thus representing better the fact that there is no unlimited resource in real life.

There are many extensions of MCLP. Dessouky (2006) and Jia et al. (2007) extend MCLP to multiple quality levels for each demand point and a number of facilities that cover each demand point for each quality level. The model is presented below.

Maximize $\sum_k \sum_{i \epsilon V} c_k d_i y_{ik}$

Subject to $\sum_{j \epsilon W_{ik}} x_j \geq Q_{ik} y_{ik}$, $i \epsilon V$, $k=1,\dots,q$

$\sum_{j \epsilon W} x_j \leq P$

$x_j, y_{ik} \epsilon \{0,1\}$, $j \epsilon W, i \epsilon V, k=1,\dots,q$

where k represents the different quality levels and it could be equal to q at most. y_{ik} is a binary variable, equal to 1 if demand point i is covered at quality level k. Unlike MCLP model, this model utilizes a term denoted as c_k instead of population which represents the importance of demand points at each quality level. In addition, Q_{ik} represents the minimum number of ambulances to be allocated to demand point i to achieve k quality level coverage. Thus, some of the demand points can be covered by multiple facilities. When determining c_k, a combination of factors such as population of the demand point, age distribution of the population, significance of the demand point, etc. can be considered. However, since this term affects the model significantly, setting the weight of the term should be conducted delicately.

Another extension of MCLP is studied by Schilling et al. (1979). They propose Tandem Equipment Allocation Model (TEAM) which includes different emergency vehicle types. This model is actually developed for fire station problems, but it is also used in ambulance allocation problems where two different types of ambulances, called Basic Life Support (BLS) Units and Advanced Life Support (ALS) Units, are available. Constraints of MCLP model are doubled, and rewritten in TEAM in terms of ambulance types A and B. Only one different constraint is added to create a hierarchy between the two types of vehicles. The mathematical formulation of TEAM is as follows:

Maximize $\sum_{i \epsilon V} d_i y_i$

Subject to $\sum_{j \epsilon W_i^A} x_j^A \geq y_i$, $i \epsilon V$

$\sum_{j \epsilon W_i^B} x_j^B \geq y_i$, $i \epsilon V$

$$\sum_{j \epsilon W} x_j^A = P^A,$$

$$\sum_{j \epsilon W} x_j^B = P^B,$$

$$x_j^A \leq x_j^B, \qquad j \epsilon W$$

$$x_j^A,\ x_j^B,\ y_i \epsilon \{0,1\}, \quad j \epsilon W, i \epsilon V$$

where $x_j^A\left(x_j^B\right)$ is a binary variable equal to 1 if a vehicle of type ALS (BLS) is located at demand point i, and the total number of vehicles of type A and B are limited by P^A and P^B.

All in all, neither LSCP nor MCLP is sufficient to respond to an additional call when the ambulance is already busy dealing with a previous call from the same coverage area. As a remedy for this unlucky situation, increasing the number of ambulances deployed may not be the only choice; however, altering the coverage strategy may also yield a solution. Multiple coverage which is a strategy to handle and to lessen the missing calls is studied for the first time by Daskin and Stern (1981) as indicated in the extensions of the LSCP model. Likewise, Hogan and ReVelle (1986) propose two models, namely, Backup Coverage Model (BACOP1 and BACOP2). Brotcorne et al. (2003) and Daskin et al. (1988) describe BACOP1 and BACOP2 models in detail and present mathematical formulations in their paper as follows:

BACOP1

Maximize $\quad \sum_{i \epsilon V} d_i u_i$

Subject to $\quad \sum_{j \epsilon W_i} x_j - u_i \geq 1, \quad i \epsilon V$

$$\sum_{j \epsilon W} x_j = P$$

$$0 \leq u_i \leq 1, \qquad i \epsilon V$$

$$x_j \geq 0, \qquad j \epsilon W$$

BACOP2

Maximize	$\theta \sum_{i \epsilon V} d_i y_i + (1-\theta) \sum_{i \epsilon V} d_i u_i$	
Subject to	$\sum_{j \epsilon W_i} x_j - y_i - u_i \geq 0$,	$i \epsilon V$
	$u_i - y_i \leq 0,$	$i \epsilon V$
	$\sum_{j \epsilon W} x_j = P$	
	$0 \leq u_i \leq 1,$	$i \epsilon V$
	$0 \leq y_i \leq 1,$	$i \epsilon V$
	$x_j \geq 0,$	$j \epsilon W$

The objective of these models is to maximize the coverage of demand points more than once. In BACOP1 model, twice coverage is maximized, while in BACOP2, both once and twice coverage are maximized using a weight θ and (1- θ) respectively where $0 \leq \theta \leq 1$. In both models, all demand points are covered at least once.

Maximal Covering Location-Allocation Problem (MCLAP) is developed by Marianov and Serra (1998) which is the queuing version of MCLP. In this model, waiting time in queue is used as a constraint.

Marianov and Serra (2001) later set forth the hierarchical queuing maximum covering location problem (HiQ-MCLP), which proposes to maximize demand covered by a two-level service. However, in this model, a demand point needs to receive low-level and high-level services, and also it has to wait in the queue for no more than b other emergency call requests, in order to be considered as “covered”.

Another extension of MCLP is introduced by Alsalloum and Rand (2003) who develop Goal Programing models. In their model, firstly location of the ambulance stations are determined to maximize the expected demand coverage, and then the number of ambulances for each station is determined according to the minimum service requirements.

Karasakal and Karasakal (2004) propose another extension of MCLP with partial coverage (MCLP-P). They use a sigmoid function to model the decrease in the coverage when the distance increases, instead of modeling as only "covered" or "not covered" for a demand point. Mathematical formulation of this model is presented below.

MCLP-P

Maximize $\sum_{i \in V} \sum_{j \in W_i} C_{ij} z_{ij}$

Subject to $\sum_{j \in W} x_j = P$

$\sum_{j \in W_i} z_{ij} \leq 1$, $i \epsilon V$

$z_{ij} \leq x_j$, $i \epsilon V$, $j \in W_i$

$x_j \epsilon \{0,1\}$, $j \epsilon W$

$z_{ij} \epsilon \{0,1\}$, $i \epsilon V$, $j \in W_i$

where z_{ij} is equal to 1 if demand point *i* is partially or fully covered by facility at j, and if $r_1 < t_{ij} < r_2, C_{ij} = f(t_{ij})$; C_{ij} is equal to 1 if $t_{ij} < r_1$.

Drezner et al. (2010) propose the stochastic version of the partial coverage model by defining the distance standards (r_1, r_2) as random variables.

Erkut et al. (2007) suggest a new model by adding a survival function to the classical coverage model, MCLP. Survival function, which is the monotonic decreasing function of the response time, allows for the calculation of the expected number of survivors in the case of emergency.

Berman et al. (2010) develop the Cooperative Maximal Covering Location Problem (CMCLP) as an extension of MCLP by using the same approach as in the Cooperative Location Set Covering Problem (CLSCP).

MCLP and its extensions discussed above are listed in Table 2.2.

Table 2.2. MCLP Model and Extensions

Authors	Year	Model	Authenticity
Church and ReVelle	1974	MCLP	Maximizing demand coverage
Dessouky and Jia et al.	2006/ 2007	Modified MCLP	Multiple quality levels for each demand point and multiple facilities at each quality level
Schilling et al.	1979	Tandem equipment allocation model (TEAM)	Two types of ambulances
Hogan and ReVelle	1986	Backup Coverage Model (BACOP)	Twice coverage
Marianov and Serra	1998	Maximal Covering Location-Allocation Problem (MCLAP)	Waiting time in queue as a constraint
Alsalloum and Rand	2003	Goal Programming Approach to MCLP	Firstly deciding the number of ambulances, then allocation of them to the stations
Karasakal and Karasakal	2004	Partial Coverage (MCLP-P)	Using sigmoid function
Drezner et al.	2010	Stochastic Version of MCLP-P	Defining distance standards as random variables
Erkut et al.	2007	Maximum Survival Location Problem (MSLP)	Using monotonic decreasing function of response rate as a survival function
Berman et al.	2010	Cooperative Maximal Covering Location Problem (CMCLP)	Threshold distance for demand coverage

2.3. Double Standard Models (DSM)

Double Standard Model (DSM) is the other main approach to EMS problems, developed by Gendreau el al. (1997). The objective and constraints are similar to the previous models, but it has a different structure in terms of using two coverage standards, r_1 and r_2 time units ($r_1 < r_2$). This idea of utilizing two different time units is especially useful for covering demand points twice. Instead of covering all with in the shorter time unit with the available ambulances, a percentage α of the population is covered within a shorter time unit, while guaranteeing the coverage of all within the longer time unit. Furthermore, by defining the objective function as maximizing the number of nodes covered by two ambulances within the shorter time unit, it is aimed that covering demand points twice within the shorter time unit is achieved as much as possible with the available ambulances.

DSM

Maximize	$\sum_{i \epsilon V} d_i y_{i2}$	
Subject to	$\sum_{j \epsilon W_{i2}} x_j \geq 1$,	$i \epsilon V$
	$\sum_{i \epsilon V} d_i y_{i1} \geq \alpha \sum_{i \epsilon V} d_i$	
	$y_{i2} \leq y_{i1}$,	$i \epsilon V$
	$\sum_{j \epsilon W_{i1}} x_j \geq y_{i1} + y_{i2}$,	$i \epsilon V$
	$\sum_{j \epsilon W} x_j = P$	
	$x_j \leq P_j$,	$i \epsilon V$
	y_{i1} , $y_{i2} \epsilon \{0, 1\}$,	$i \epsilon V$
	x_j integer,	$j \epsilon W$

where y_{ik} is equal to 1 if the demand at node i is covered k times (k=1 or 2) within shorter time unit, and x_j again represents the number of ambulances located at node j.

Doerner et al. (2005) extend the DSM by using penalty terms in the objective function. The first term is the total number of demand points not covered within the large time unit. The second penalty term is defined as the deviation from covering all the demand with a probability determined by the shorter time unit. The last one is for every demand point; that is the deviation of work load per facility, which is assigned to that demand point to be covered in longer time unit, from a predetermined standard (w_0). These penalty terms are formulated as follows:

$$f_1 = \left|\left\{i \in V:\ \sum_{j \in W_{i2}} x_j = 0\right\}\right|$$

$$f_2 = \alpha - \min\left(\alpha,\ \frac{\sum_{i \in V} d_i y_{i1}}{\sum_{i \in V} d_i}\right)$$

$$f_3 = \sum_{i \in V}\left(\frac{d_i}{\sum_{j \in W_{i2}} x_j} - w_0\right)^+$$

These functions are added to the objective of DSM model by assigning different values for M_1, M_2, and M_3, that the decision makers can determine the relative importance of.

Maximize $\quad \sum_{i \in V} d_i y_{i2} - M_1 f_1 - M_2 f_2 - M_3 f_3$

They add these three functions as constraints to the model instead of the first two constraints of DSM.

Another extension of DSM is the Dynamic Double Standard Model (DDSM) suggested by Gendreau et al. (2001) that will be explained in detail in section 2.6.

DSM and its extensions discussed above are listed in Table 2.2.

Table 2.3. DSM and Extensions

Authors	Year	Model	Authenticity
Gendreau el al.	1997	DSM	Introducing two different time units
Doerner et al.	2005	Extended DSM	Adding penalty terms to the objective of DSM
Gendreau et al.	2001	DDSM	Dynamic DSM by adding penalty terms for relocations

2.4. Maximum Expected Covering Location Problems (MEXCLP)

Until the development of MEXCLP, many models are deterministic with the exception of some extensions. Missing calls are assumed to be handled by multiple coverage strategies. However, probabilistic methods are strong tools to handle missing calls as they make it possible to use the busy probability of the ambulances.

Maximum Expected Covering Location Problem (MEXCLP) is one of the first probabilistic models introduced by Daskin (1983). In spite of the fact that this is probabilistic, it can be considered as an extension to MCLP. In the model presented below, q represents the busy probability of the ambulances, and the objective is to maximize the expected demand coverage which is E_k=$d_i(1-q^k)$. This expected value is involved in the objective as the marginal contribution of the k^{th} ambulance, which is $E_k - E_{k-1} = d_i(1-q)q^{k-1}$. The model assumes that busy probability is independent among facility points, and that every ambulance has the exact same busy probability.

Maximize $\sum_{k=1}^{P} \sum_{i \epsilon V} d_i(1-q)q^{k-1}y_{ik}$

Subject to $\sum_{j \epsilon W_i} x_j \geq \sum_k y_{ik}$, $i \epsilon V$

$\sum_{j \epsilon W} x_j \leq P$

$y_{ik} \epsilon \{0,1\}$, $i \epsilon V$, $k=1,\ldots,p$

x_j , integer, $\quad j \in W$

where y_{ik} is a binary variable, equal to 1, if demand point *i* is covered by at least *k* facilities.

Moreover, Daskin et al. (1988) summarize the similarities and differences between the set covering and maximal covering models, and their extensions that consider the ambulances being busy. In their study, they also recommend using a different time standard for each number of times a node is covered.

Adjusted MEXCLP (Batta et al. 1989) is a model that seeks to handle the assumptions of MEXCLP by combining the optimization technique with the hypercube queuing theory. Contrary to the MEXCLP, it does not assume independence between ambulances and facility locations, and every ambulance has its own busy probability. Utilization of this hypercube queuing theory, which treats ambulances as servers, provides useful data regarding ambulances and demand points. This model has an additional correction factor in the objective that corrects the independence argument developed by Larson (1975). If the correction factor equals 1, Adjusted MEXCLP exactly behaves like MEXCLP.

Another extension of the MEXCLP, TIMEXCLP is developed by Repede and Bernardo (1994). As can be deduced from its name, this model is an enhanced version of MEXCLP for time periods. In this model all the parameters and the decision variables of the MEXCLP model are redefined for each period *t*.

Maximize $\quad \sum_{t=1}^{T} \sum_{k=1}^{p_t} \sum_{i \epsilon V} (d_{i,t})(1-q_t)q_t^{k-1} y_{i,k,t}$

Subject to $\quad \sum_{j \epsilon W_{i,t}} x_{j,t} \geq \sum_{k=1}^{p_t} y_{i,k,t}$, $\quad i \in V$, $t \leq T$

$\sum_{j \epsilon W} x_{j,t} \leq p_t$, $\quad t \leq T$

$y_{i,k,t} \in \{0,1\}$, $\quad i \in V$, $k=1,\dots,p_t$, $t \leq T$

$x_{j,t}$, integer, $\quad j \in W$, $t \leq T$

On the other hand, Saydam and Aytuğ (2003) study the objective function of the MEXCLP in a nonlinear form. Mathematical formulation of this new model is presented below.

Maximize $\quad \sum_{i \epsilon V} d_i \, (1-q)^{y_i}$

Subject to $\quad \sum_{j \epsilon W_i} x_j = y_i \,, \qquad i \epsilon V$

$\sum_{j \epsilon W} x_j \leq P$

x_j, y_i , integer , $\qquad j \epsilon W, i \epsilon V$

They use an approximation for the nonlinear objective function. It is incorporated into the following function as:

$$\sum_{i \in V} d_i \left(1 - \prod_{j \in w_i} q^j\right)$$

According to the paper, this new model performs better than MEXCLP in estimating the coverage rate.

Iannoni and Morabito (2007) study a complex situation which handles different types of calls and different types of ambulances. Therefore, different types of calls are responded by different types and numbers of ambulances.

MEXCLP2 (McLay, 2009) is a model which uses similar assumptions and solution strategies to the adjusted MEXCLP. However, this model uses two different types of ambulances and more than one type of patients (corresponding to call priorities).

MEXCLP models, especially by taking into account incidences when ambulances are busy, reflect better sense of the real world when compared to the deterministic models. Nevertheless, it has its own complication of requiring estimation of data related to “busy probability” and “expected coverage”. Aside from reflecting the real world, an erroneous estimation of these parameters may even yield irrelevant and imprecise results.

In Table 2.4, we outline the MEXCLP models and its extensions.

Table 2.4. MEXCLP Model and Extensions

Authors	Year	Model	Authenticity
Daskin	1983	MEXCLP	Busy probability of the ambulances
Batta et al.	1989	Adjusted MEXCLP	Relaxing independence assumption between ambulances
Repede and Bernardo	1994	TIMEXCLP	Multi period MEXCLP
Saydam and Aytuğ	2003	Nonlinear MEXCLP	Nonlinear objective function
Iannoni and Morabito	2007	Modified MEXCLP	Different types of calls, different types of ambulances
McLay	2009	MEXCLP2	Different types of calls, two types of ambulances

2.5. Maximum Availability Location Problem Models (MALP)

Maximum availability location problem (MALP) model, which is developed by ReVelle and Hogan (1989a), is another probabilistic approach in the EMS literature. In these models, it is aimed to maximize the coverage of the demand by a specific probability of α. There are two types of this model; these are MALP-I and MALP-II. In the MALP-I, all ambulances have the same busy probability q, and these are independent of each other. The following function is constructed to determine the required number of facilities covering each demand point to provide α probability level;

$1 - q^{\sum_{j \in W_i} x_j} \geq \alpha$ and this is linearized as;

$$\sum_{j \in W_i} x_j \geq \left\lceil \frac{\log(1-\alpha)}{log\ q} \right\rceil = b$$

So, the following model gives the solution whether the demand points are covered b times at α probability level and the opening decisions of facilities that serve these demand points. y_{ik} is again defined as in the MEXCLP model, and equals 1 if demand point i is covered by at least k facilities.

MALP-I

Maximize $\sum_{i \epsilon V} d_i y_{ib}$

Subject to $\sum_{j \epsilon W_i} x_j \geq \sum_{k=1}^{b} y_{ik}$, $\quad i \epsilon V$

$y_{i,k+1} \leq y_{ik}$, $\quad i \epsilon V$, $k=1,\ldots, b-1$

$\sum_{j \epsilon W} x_j = P$

$x_j, y_{ik} \epsilon \{0,1\}$, $\quad j \epsilon W, i \epsilon V, k=1,\ldots, p$

In MALP-II, busy fraction q_i is used for each demand point although in the MALP-I, all ambulances have the same busy probability q. Since pre-determining busy probability for each of the demand points is a hard work, using iterative process for estimating these values may provide a more convenient way (ReVelle and Hogan, 1989a).

Queuing maximal availability problem (Q-MALP) is an extension of MALP model which is suggested by Marianov and ReVelle (1996). This model makes the same assumption as in the MALP model regarding the ambulances operating independently from each other. Instead of the b term in the MALP model, this model has the b_i term which is calculated separately for each demand point. EMALP developed by Galvao et al. (2005), on the other hand, extends the assumption stating that the ambulances are identical in the MALP model by integrating a hypercube model into the MALP. Since the model necessitates defining each ambulance separately, assigned to each single facility, the x_j term evolves into x_{jk} which is equal to 1 if facility k is located at j. Besides, a correction factor is added in the Adjusted MALP model like in the Adjusted MEXCLP model.

MALP model and its extensions are listed in Table 2.5.

Table 2.5. MALP Model and Extensions

Authors	Year	Model	Authenticity
ReVelle and Hogan	1989a	MALP-I	Covering b times with α probability level by using independent busy fraction of ambulances
ReVelle and Hogan	1989a	MALP-II	Covering b_i times with α probability level by using busy fraction of ambulances
Marianov and ReVelle	1996	Q-MALP	Relaxing the independence assumption using queuing system
Galvao et al.	2005	EMALP	Relaxing the identical ambulances assumption by using hypercube theory

2.6. Dynamic Allocation and Relocation Models

Static models, in which numbers of ambulances and places where they reside are fixed at the first stage have some flaws at the operational level in terms of flexibility despite yielding good results from a strategic point of view. Determining the initial positions of the ambulances seems to be a critical problem; however, fixing them at certain positions at all times may not be as effective as expected in real life cases.

Many models in the literature treat demand points as static assets, and arrange ambulance locations and allocations accordingly. On the other hand, population density may vary within a day or due to seasonal causes. For example, population is denser around business centers during daytime, and shifts to residential areas at night. Holiday destinations observe a huge increase in population during summers, but they are relatively deserted in winter. In such cases, holding the ambulance distributions at their initial positions at all times may not prove to yield effective results. A need for shifting the ambulances from low demand points to higher demand points emerges then. In this case, how and according to what scheme places and numbers of these ambulances will be modified is another problem to be modeled.

Gendreau et al. (2001) suggest the first real time EMS facility relocation model by converting their previous work, DSM, to a dynamic version, which is called the Dynamic Double Standard Model (DDSM). They model the dynamic nature of the model by adding the penalty term for the relocations of the ambulances to the objective function using the parameter, M_{jk}^{t}, which is equal to the cost of repositioning for ambulance *k* from its current site to site *j* at time *t*. This term restricts the unnecessary movements of the ambulances. Other variables, parameters, and the constraints of this model can be interpreted as in the static model, DSM.

DDSM

Maximize $\quad \sum_{i\in V} d_i y_{i2} - \sum_{j\in W} \sum_{k=1}^{p} M_{jk}^{t} x_{jk}$

Subject to $\quad \sum_{j\in W_{i2}} \sum_{k=1}^{p} x_{jk} \geq 1, \qquad i \in V$

$\sum_{i\in V} d_i y_{i1} \geq \alpha \sum_{i\in V} d_i$

$y_{i2} \leq y_{i1}, \qquad i \in V$

$\sum_{j\in W_{i1}} \sum_{k=1}^{p} x_{jk} \geq y_{i1} + y_{i2}, \qquad i \in V$

$\sum_{j\in W} x_{jk} = 1, \qquad k=1,\dots,p$

$\sum_{k=1}^{p} x_{jk} \leq P_j, \qquad j \in W$

$y_{i1}, y_{i2} \in \{0,1\}, \qquad i \in V$

$x_{jk} \in \{0,1\}, \qquad j \in W, k=1,\dots,p$

Schmid and Doerner (2010) suggest the multi period version of DDSM by using time dependent travel times, called mDSM. This model has the ability to provide coverage during the whole planning horizon and arrange the relocation of ambulances.

Gendreau et al. (2006) suggest a model, namely Maximal Expected Coverage Relocation Problem (MECRP). In this model, idle ambulances in low demand areas are relocated without exceeding a predefined value for the number of relocations.

Dynamically Available Coverage Location (DACL) is another dynamic model in the EMS literature developed by Rajagopalan et al. (2008). The model is solved by incorporating hypercube theory using time-varying demands and independent busy probabilities.

Schneeberger et al. (2014) build a two stage relocation model where ambulances are relocated in the presence of a crisis situation. In this paper, firstly, a location model based on an existing model, mDSM, is used to locate ambulances at potential facilities. Then a relocation model is introduced to relocate the remaining ambulances after necessary ambulances are occupied for the crisis case (such as traffic accidents).

Maleki et al. (2014) propose two new models for redeployment of ambulances. In this paper, they use an existing model, MECRP, to locate ambulances initially, and they propose Generalized Ambulance Assignment Problem (GAAP) which minimizes the total travel time of the ambulances, and Generalized Ambulance Bottleneck Assignment Problem (GABAP) which minimizes the maximum travel time.

Jastenberg et al. (2015) develop an algorithm, namely dynamic MEXLP heuristic, for dynamic ambulance redeployment by minimizing late arrivals. They demonstrate that the proposed heuristic algorithm reduces the expected fraction of late arrivals by 16.8% and also reduces the general response time significantly.

Table 2.6 summarizes dynamic allocation and relocation models.

Table 2.6. Dynamic Allocation and Relocation Models

Authors	Year	Model	Authenticity
Gendreau et al.	2001	Dynamic Double Standard Model (DDSM)	Penalty term to the objective for the relocations of the ambulances
Schmid and Doerner	2010	Multi period version of DDSM (mDSM)	Using time dependent travel times
Genreau et al.	2006	Maximal Expected Coverage Relocation Problem (MECRP)	Relocation of the idle ambulances using an upper limit for the number of relocations
Rajagopalan et al.	2008	Dynamically Available Coverage Location (DACL)	Incorporating hypercube theory using time-varying demands
Maleki et al.	2014	Generalized Ambulance Assignment Problem (GAAP)	Minimizing the total travel time of the ambulances in relocation (firstly use MERCP)
Maleki et al.	2014	Generalized Ambulance Bottleneck Assignment Problem (GABAP)	Minimizing the maximum travel time in relocation (firstly use MERCP)
Jastenberg et al.	2015	Dynamic MEXLP	Dynamic ambulance redeployment by minimizing late arrivals

2.7. Other Studies in the EMS Literature

Beraldi et al. (2004) suggest an approach to design the robust emergency medical services by using stochastic programming. This model determines the ambulance locations and the number of them at each location to achieve a reliable service level, and the minimum cost as well by using probabilistic constraints.

Another study by Coşkun (2007) includes an integer programming model that minimizes cost by determining the number of stations, ambulances, their locations to cover the demand in the system. Then this model is applied for the city of Adana emergency medical service system by solving it using a genetic algorithm.

Sorensen and Church (2010) introduce a new model, namely LR-MEXCLP model, to the literature which is a hybrid model combining the local busyness estimate of MALP model with the maximum coverage objective of MEXCLP model. They compare their model with MALP and MEXCLP models, and submit the results of these studies.

2.8. Simulation Studies for the EMS

Goldberg et al. (1990) develop a simulation model to compare two alternative sets of ambulance locations in Tucson. They mainly describe their simulation model development, data collection and model validation by checking some performance measures such as successful service rate to calls.

Repede and Bernardo (1994) develop a decision support system that includes a mathematical model developed also in this paper (TIMEXCLP), and a simulation model. They apply the new approach to the Louisville (Kentucky) EMS System, and prove the 13% increase in demand coverage and 36% decrease in response time without any increase required in the resources.

Another study related to using simulation in EMS operations is conducted by Christie and Levary (1998). They develop a simulation model using an illustrative example. In addition, they perform what-if analyses to predict the possible scenarios and demonstrate the results supporting the advantages of the simulation model in the EMS operations.

Ingolfsson et al. (2003) develop a simulation model to test single start station system (SS system) in the city of Edmonton EMS department. Moreover, they use this model to observe other changes in the EMS operations, such as addition of station and ambulances, different shifts and relocations. The results on these studies are summarized in the paper. Their study also includes the development and the validation of the simulation model.

Another simulation study utilized in EMS operations is conducted by Kozan and Mesken (2005). Their aim is to develop and test a simulation model to analyze the effects of emergency calls, resources used, response times, and ambulance location and allocation method. An application is conducted using hypothetical data to test several scenarios in the Ambulance System. So, they propose that the model is used for many emergency centers by using realistic parameters with some changes in the model.

Aringhieri et al. (2007) develop integer linear programming models to locate ambulance stations after analyzing the emergency system with real life data. They also test the behavior of their solution by using a simulation model, since such mathematical models use some simplifications with respect to real life situations. Furthermore, they use this approach in Milano city case in order to show the importance of the approach and make some suggestions for the EMS management.

Another study is submitted by Sullivan (2008) that includes a discrete event simulation study for the rural emergency medical services during disasters.

Wu and Hwang (2009) develop a discrete-event simulation to improve the ambulance response time by balancing ambulance availability. Their main objective is to estimate the threshold for the number of ambulances with respect to demand increases, and to find the optimal allocation strategies for the temporary decreases in ambulance availability. This simulation model is applied to the EMS system of Tainan City for the purpose of validation. They confirm that the model represents the actual Tainan EMS system by using statistical analysis, and suggest some dispatching strategies to minimize the response time.

Zhen et al. (2014) propose a simulation optimization method that allows for assessing the performance of the ambulance distribution plan by using a simulation model. Simulation optimization algorithm is based on the use of a genetic algorithm and simulation model iteratively. An application example from the city of Shanghai is given to show the usage of the proposed approach. In addition, validation of the proposed approach is conducted by using some numerical experiments.

Pinto et al. (2015) conduct a general study on how to construct a simulation model of the EMS systems. They propose a method to build a generic simulation model to analyze EMS systems. In addition, they discuss the most important input data and performance measures in order to establish a reliable simulation model. Furthermore, they validate their proposed method by testing their simulation against real world data, and present the results.

In addition, a review study on simulation models is conducted by Aboueljinane et al. (2013), in which they bring together the simulation models on the EMS literature. They compare and contrast the models with respect to many aspects and features.

In most of the covering models, a demand point can be considered as covered when at least an EMS vehicle can reach an emergency call within a predefined distance. Earlier studies do not consider responding to an additional call when an ambulance is busy. Therefore, multiple coverage idea is introduced to overcome this drawback of the initial models. A larger number of demand points are backup covered with different time standards based on this idea. On the other hand, other models are introduced to handle this issue by utilizing busy probabilities of the ambulances and reliability of the facilities. These probabilistic models are better than the deterministic models in the determination of the number of ambulances needed, and estimation of the demand coverage. Moreover, dynamic models achieve better coverage by using time dependent parameters in a more realistic way (Li et al., 2011). However, dynamic models require excessive processing power and some optimal searching techniques such as heuristics, and metaheuristics.

According to this review, we use static mathematical models instead of dynamic models. On the other hand, since it is obvious that the nature of the EMS problems is stochastic, we also use a simulation model to reflect the real EMS system better. Moreover, MEXCLP model, one of the probabilistic static models in the literature, which uses busy probabilities of the EMS vehicles, can be considered to be suitable for using together with a simulation model.

CHAPTER 3

PROBLEM DEFINITION

3.1. Definition of the Emergency Medical Service Environment

In the Emergency Medical Service (EMS) problem environment, the elements of the system should be identified first. When an incident occurs, emergency medical service is requested by a phone call, whose number is set as 112 in Turkey. All calls are answered by one centralized department at each region or city, which is the control center (CC). The CC directs a suitable ambulance to the place of the incident from a close emergency medical service station, such as medical institutions or buildings serving this purpose, where ambulances wait ready for dispatch. After the ambulance arrives at the incident scene, the medical treatment is conducted there or on the way to the hospital by the ambulance medical technicians. Patients requiring advanced medical treatment are reported to the CC. At this point, if required, ambulance crew may make an inquiry about the nearest or most convenient medical institution (Resmi Gazete, 2000). Hence, arguably the most important component of the system is the CC.

CC staff, namely CC doctors or call center people, carry out some very critical duties. Their most important duty is to answer and assess the incoming calls, and to dispatch ambulances to the place of the incident as needed, after deciding for the appropriate medical service as a result of the assessment. This assessment process includes determining the severity and degree of the case, called triage, the quantity and type of the ambulances, as well as the stations from which the ambulances are to be dispatched. The number of patients or wounded people is also among the information obtained during triage. Moreover, the CC doctor decides whether emergency medical treatment is necessary; and if it is not, CC doctor informs the caller about how the request will be resolved (Resmi Gazete, 2000). Consequently, many studies on EMS system focus mainly on the processes, call arrivals, assessment of the calls, and dispatching of the ambulances to the incident scene.

As expected, ambulance dispatch is affected by the location of the emergency medical service stations. Thus, the location of emergency service stations and the number of ambulances at the stations are determined in a way to reach the incident place within the necessary time standard. This time is called the response time, which is determined by the international standards as 10 minutes for urban areas, and 20 minutes for rural areas (Acil Sağlık Hizmetleri, 2011)

Ambulance types can differ according to the characteristics of the incident such as ambulances with doctors, and ambulances with other medical personnel (Resmi Gazete, 2000). Although in many of the incidents, one ambulance turns out to be sufficient, severity level of an incident or some crisis situation may necessitate more than one ambulance.

Ambulance service, most important part of the EMS systems, has some similarities with fire and police services, but there are some differences from the operational perspective. It is not an obligation for ambulances to have a station such as buildings; they wait for an emergency case parking in an ordinary place, because parking site does not directly affect their service quality. After all, their primary goal is to reach the incident site they serve in the required time as quickly as possible. In addition, the locations and the number of ambulances at the stations can be rearranged over time. One example to this is the redeployment of ambulances at the cities and towns which have seasonal population over the year, or at the regions with varying population between day and night time.

Occasionally, ambulances are assigned for a new emergency call while en route to the station from a previous emergency service. However, it is very difficult to reflect this situation theoretically in our solution approaches which requires usage of advanced technologies such as geographic information systems.

3.2. Issues in Ambulance Service Systems

Before studying the location of EMS vehicles and handle the problem in detail, some important considerations should be made. Firstly, the number of ambulances and the locations of stations where the ambulances reside should be determined. The locations of stations are selected among several alternative facilities. Some considerations in this context are: whether the facilities must be selected from among the already existing locations, or if some new locations are needed, or even if some existing facilities need to be closed as they are no longer suitable. These considerations and resulting actions may be hard to implement, or may not be feasible due to various reasons such as economic or political ones; and hence one must always take these constraints into account when making assumptions and deriving results.

After making the decision regarding facility location alternatives, the next decision is how the ambulances are distributed among the facilities. Ambulance allocation problems such as how many ambulances and which type of ambulances are to be placed at each facility, their service responsibility areas and response times in providing services need to be addressed.

Yet another matter of discussion is on the maximum allowable response time. Although it is set by the international standards, as stated before, due to the constraints on the number of the ambulances or the occasional shortage of available ambulances as they are on duty dealing with other incidents, keeping up with the international standards may turn out to be very difficult, and sometimes even impossible. Under these circumstances, putting a margin of deviation from the international standards should be considered. Also how much deviation can be tolerated, for what type of calls, and in what regions are the other questions yet to be addressed.

As stated before, calls are processed by the CC. However, quality of how these calls are resolved need to be assessed, and the information obtained during triage about the patients and the emergency incident need to be questioned regarding reliability. Patient's relatives or reporting people can misguide the CC unintentionally, as they lose composure or may intentionally exaggerate the situation to get better or faster service. Hence, these and similar types of events must be elaborated, as the information obtained during the triage is a major factor both in ambulance deployment and the resulting maximum response time.

One of the most important problems is the situation when the ambulance that may respond to an emergency in time is busy dealing with another incident. Precautions and strategies need to be developed and have to be put into action against this.

Finally, a point to mention is that when making decisions, difficulties of the practical real world should be taken into account such as ownership of the ambulances (either government or private sector), the difficulties of data acquisition, not only for triage but also for issues such as tracking the number and region of the calls, and the difficulty of managing to accomplish many conflicting objectives such as trying to respond to emergencies as fast as possible, while deploying that many ambulances becomes very costly.

CHAPTER 4

MATHEMATICAL MODEL FOR THE LOCATION-ALLOCATION OF AMBULANCES

In this chapter, we address the problem of the location-allocation of ambulances which we call ‘Gradual Maximum Expected Covering Location Problem’. We formulate this problem as an integer programming model. Then we provide the validation and implementation phases of this integer program.

4.1. Gradual Maximum Expected Covering Location Problem

The mathematical model developed in this study can be considered an extension of the Maximum Expected Covering Location Problem (MEXCLP) model proposed by Daskin (1983), combined with a feature of the Double Standard Model developed by Gendreau et al. (1997), also including the multiple coverage idea with different time standards that was first discussed by Daskin et al. (1988). The idea in this model is to cover a node multiple times by using different time standards, and to make some proportion of demand covered for each or desired coverage times.

By using this idea, the model first maximizes the primary coverage in the most desirable time standard, then maximizes the twice and other extra coverage times up to total number of ambulances in more relaxed time standards. Coverage times are represented by the k term which may get at most the value P (total number of ambulances), thus, a demand point can theoretically be covered P times at most. A time interval is defined for each level k. A more detailed explanation is provided as follows:

For k=1, a demand point should be covered by at least one ambulance in time $t_0=0 < t \leq t_1$, For k=2, a demand point should be covered by at least two ambulances in time $t \leq t_2$,

For k=3, a demand point should be covered by at least three ambulances in time $t \leq t_3$, …

For k=P, a demand point should be covered by P ambulances in time $t \leq t_P$.

Geographical representation of coverage levels for demand point i is depicted in Figure 4.1.

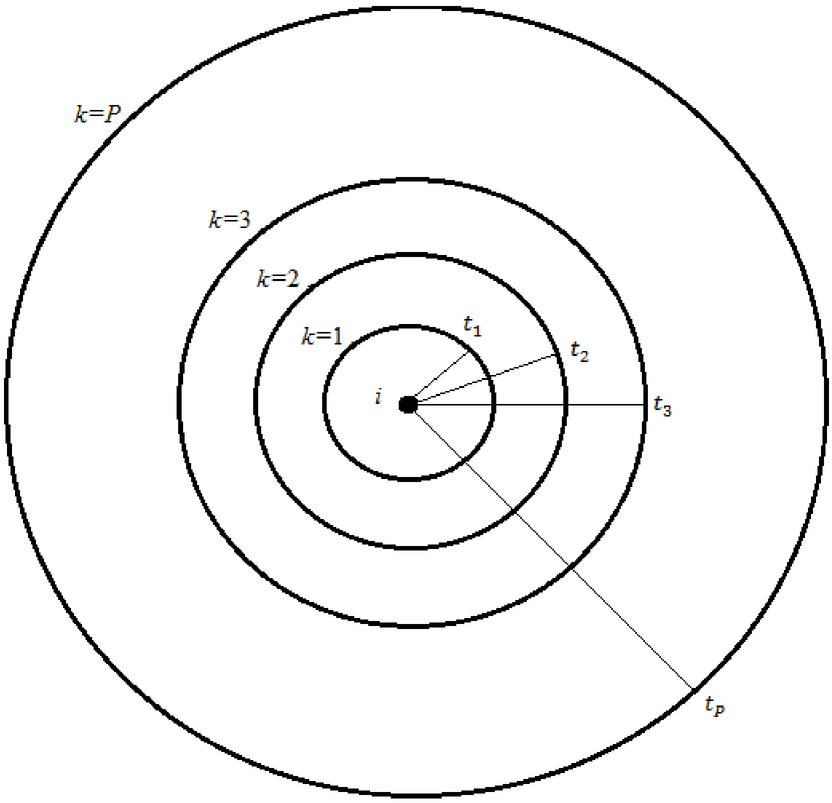

Figure 4.1. Graphical Representations of the Coverage Levels

One of the main features of this model is that it tries to cover a demand point within the minimum time; however, if this cannot be achieved with the resources at hand, it offers the opportunity to stretch out the response time on the condition that the number of coverages of the demand point is increased as well. In this manner, it is ensured that the disadvantages of demand points that cannot be covered in shorter time units are compensated for by covering them with multiple ambulances but in longer time units.

The other powerful features of the model can be described as follows: it tries to cover all demand points as many times as possible in harmony with the equity feature feature. This means that the model does not exclude the low demand points, while it favors to cover high demand points. Nevertheless, demand points which have higher demands are covered with more ambulances due to the characteristics of the objective of the model on the condition that all demand points should be covered at least at one of the many coverage levels.

In addition, we try to cover the desired proportion of demand (for each coverage level, k), so then it is possible to set a coverage lower limit for coverage times that are appreciated the most. Minimum coverage percentage for each level (percentage covered at least once in time less than time, t_1, covered at least twice for t_2 , etc.) can be set by the decision maker, if required.

The mathematical model is constructed as an integer programming model. Detailed definition of the model can be seen in the following sections.

4.1.1. Assumptions and Notation

<u>Assumptions</u>

- Demand points correspond to an aggregated population area such as district, neighborhood, etc.
- Total ambulance demand is directly used, if there exists the number of call information for each demand point, or determined based on the population of each demand point.
- Busy fraction of each ambulance (q) is calculated based on the average duration of a single call, total demand, and number of ambulances.
- One type of call is assumed; triage is not made and each call has the same weight.

- Travel times between nodes are calculated by directly using distance measures; traffic density or other obstacles affecting travel times are not considered in travel time estimation.
- The average travel time between demand points and facilities is assumed to be known or to be determined based on the distances between nodes.
- Demand points can also be an ambulance facility location site.
- One type of ambulance is used.
- More than one ambulance can be placed at any facility location site.

Sets

V	set of demand points	*i = 1,...,n*
W	set of ambulance facility locations	*j = 1,...,n*

Parameters

d_i total ambulance demand at demand point *i*

$$a_{ijk} = \begin{cases} 1, \text{if demand point } i \text{ is covered by facility at point } j \text{ within} \\ \quad \text{predetermined time interval } t \in (t_k, t_{k+1}] \text{ for level } k \\ 0, \text{otherwise} \end{cases}$$

$\propto_k$ minimum coverage requirement of total demand for each coverage level *k*

P total number of available ambulances

q busy fraction of each ambulance

Decision variables

x_j number of ambulances located at facility *j*

$$y_{ik} = \begin{cases} 1, \text{if demand point } i \text{ is covered by at least } k \text{ ambulances at the } k^{th} \\ \quad \text{and lower levels} \\ 0, \text{otherwise} \end{cases}$$

4.1.2. Formulation of the G-MEXCLP Model

Maximize $Z = \sum_{k=1}^{P} \sum_{i=1}^{n} (1-q)\, q^{k-1}\, d_i\, y_{ik}$ (1)

Subject to

$\sum_{j=1}^{k} a_{ijk}\, x_j \geq k\, y_{ik}$ $\forall\, i \in V$ and $k = 1, \ldots, P$ (2)

$\sum_{i=1}^{n} d_i\, y_{ik} \geq \alpha_k \sum_{i=1}^{n} d_i$ $\forall\, k = 1, \ldots, P$ (3)

$\sum_{k=1}^{k'} y_{ik} \geq 1$ $\forall\, i \in V$ (4)

$\sum_{j=1}^{n} x_j = P$ (5)

$x_j \geq 0$ and integer $\forall\, j \in W$ (6)

$y_{ik} \in \{0,1\}$ $\forall\, i \in V$ and $k = 1, \ldots, P$ (7)

(1) The objective is to maximize the expected coverage of the demand points. This difference is defined previously. In the MEXCLP model, there is only a single time standard and every additional ambulance covers the demand point in that time standard. On the other hand, for each additional ambulance a new coverage level is determined with a different time standard. In the objective function, $[(1-q)\, q^{k-1}\, d_i]$ the term can be considered as the coefficient of each y_{ik} term. Since the demand d_i of a point i does not change, this coefficient differs only with $[(1-q)q^{k-1}]$ which decreases when k increases. However, for large q, the difference between the coefficients will tend to decrease, as a result, forcing the model to give values to y_{ik} for large k. In this case, the model then prefers multiple coverage of the points with large demand, rather than covering other points with relatively low demand even once. This interpretation proves the importance of constraints (3) and (4) that will be described below.

In addition, if the time interval between t_1 and t_2, t_2 and t_3, and so on gets smaller, this model resembles the MEXCLP model except the constraints (3) and (4).

(2) This constraint requires that the total number of ambulances located at facilities covering a demand point i must be greater than or equal to k if the demand point is covered in the k^{th} coverage level with the k^{th} time standard. This constraint ensures to have a total of k ambulances at least at the k^{th} level or below. The rationale behind this relation of the levels and the number of ambulances is described below in detail.

- Figure 4.2 illustrates this rationale for three levels only. The first curve represents k = 1 and t=t_1, the second curve represents k=2 and t=t_2 and the third one represents k = 3 and t=t_3. In this example, y_{i1} gets a value since there is one ambulance at or under level 1. Similarly, y_{i2} and y_{i3} are also getting values as they have 2 and 3 ambulances at or under levels 2 and 3, respectively.

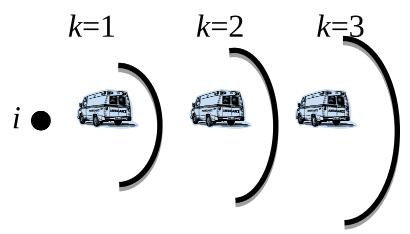

Figure 4.2. Ambulance Locations for y_{i1} = 1, y_{i2} = 1, y_{i3} = 1

- In this model, unlike MEXCLP, there is no such constraint as y_{i2} cannot have a value when y_{i1} does not have. Therefore, although y_{i1} does not get a value, y_{i2} may get a value, and occurrence of the case in Figure 4.3 is quite possible in our model.

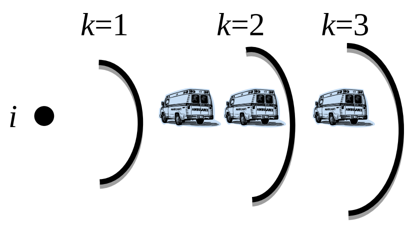

Figure 4.3. Ambulance Locations for y_{i1} = 0, y_{i2} = 1, y_{i3} = 1

- Similarly, the case below is also probable as there is no hierarchical constraint preventing this case from occurring. And respectively, the first case (Figure 4.2) causes the objective to get the maximum value, whereas the last case in Figure 4.4 makes it the minimum among the three cases considered here. It should be that noted there are 3 ambulances located at different levels for the demand point *i* in the three cases.

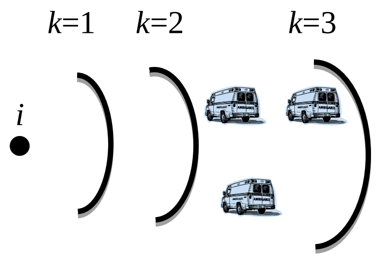

Figure 4.4. Ambulance Locations for y_{i1} = 0, y_{i2} = 0, y_{i3} = 1

Consequently, not having the hierarchical constraint for the levels provides an opportunity where even though a demand point *i* does not have any ambulances to be covered at or under time t_1, it may yet have at least 2 ambulances at or under time t_2, or 3 ambulances at or under time t_3.

(3) This constraint satisfies that α percent of the total demand should be covered for each or some coverage level *k*, and thus provides to cover the desired percent of the total demand for the preferred coverage level or levels. As an example, if 95% of the demand is desired to be covered at level 1, α_1 may be set as 0.95. As discussed before, this constraint is a means of precaution at times when the busy fraction is high, and the model prefers to cover high demand points for multiple times rather than covering each node for once. On the other hand, it may be used as an option where the decision maker favors to cover a demand point with multiple ambulances in larger time units over covering it with at least one ambulance in shorter time units. At that time, decision maker could adjust α_k as needed for large *k*; therefore, this constraint is an optional one.

(4) This constraint ensures that all demand points, no matter at which coverage level, is covered for at least one *k* (mandatory coverage). However, since implementing

this for all k is not possible theoretically (a demand point cannot be covered by all ambulances), a highest coverage limit such as k' may be determined, and y_{ik} must be nonzero for at least one of the k=1,2,…, k' levels. When determining k', the maximum allowable response time for a demand point set by the decision maker is also of importance. Hence, if the decision maker wants to have a demand point to be covered by time unit $t_{k'}$ at most, then k' in this constraint can be set accordingly. Still, the minimum number of ambulances to realize this constraint is critical.

It may be necessary to exclude this constraint if the model does not give a feasible solution with the number of available ambulances, and the number of ambulances cannot be increased. As stated above, the reason to add this constraint to the model is to ensure that there is not any demand point left uncovered with any one of the levels. Hence, this model does not ignore the low demand points such as the rural areas with less population while giving importance to high demand points.

(5) This constraint implies that total number of the ambulances in the system should be equal to P.

(6) This constraint provides that x_j is an integer.

(7) Finally, y_{ik} is defined as a binary variable in the last constraint.

4.2. Model Validation

4.2.1. Computational Results Using Test Problems

4.2.1.1. Data

G-MEXCLP model is tested using the maximal covering test problems data available on http://www.lac.inpe.br/~lorena/instancias.html. They represent real data collected at the central area of the Sao Jose dos Campos city (Brazil) for the problem to find locations for antennas. Test data include the coordinates of the 323 demand points and total demand of each point. This total demand is considered as monthly demand in this study. Coordinates of points and demand of each point are submitted in Table B.1. in Appendix B. Euclidian distance is used to calculate the average distance between each pair of demand points as many of the studies in the literature frequently use (Fujiwara et al.,1987), (Aringhieri et al., 2007), and (Silva and Pinto, 2010). Then these distances are scaled to be used for our ambulance location problem. In order to find the average travel time between demand points, average velocity of the ambulance is assumed as 60 km/h similar to previous studies (Felder and Brinkmann, 2002). So, the travel times between demand points are obtained using distances between nodes and average velocity of the ambulance. The distribution of these points on the X-Y plane is illustrated in Figure 4.5 (unit in meters).

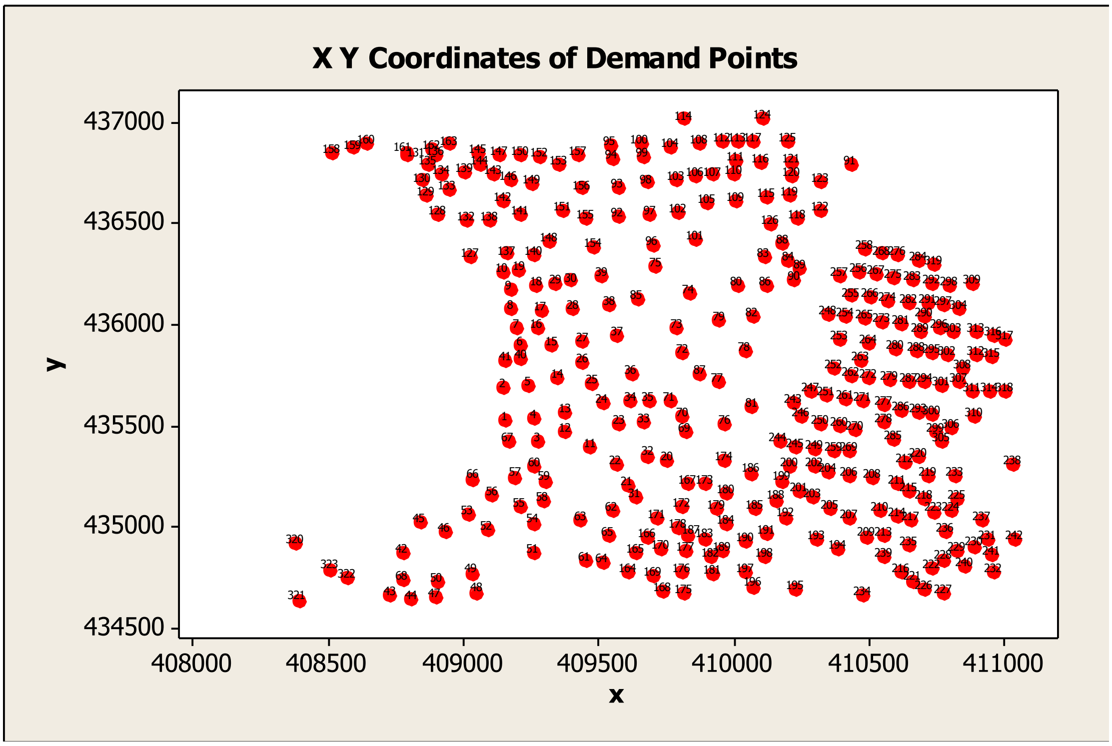

Figure 4.5. Spatial Distribution of Demand Points

4.2.1.2. Initial Values of the Parameters

When solving the test problems, k values are limited as k=1,2,3,4,5 of its theoretical span k=1,2,…,P. t_k values are set considering characteristics of average travel time matrix, namely, as t_1=6 min, t_2=9 min, t_3=12 min, t_4=15 min, and t_5=18 min and the parameters, a_{ijk} are used in the model based on the t_k values for each k. On the other hand, k' value is set as 3, meaning that maximum response time of a demand point is set to be 12 min. Demand of every point is already included in the data set and used as is. This data can be viewed in Table B.1 in Appendix B.

α_k values are assumed to be zero initially, and the model is run to see the percentage of covered demand at each level. Afterwards, some values are assigned to α_k as needed.

As stated before, there is a minimum number for ambulance fleet size that satisfies the constraints of the model. However, it is difficult to decide since there are more than one time standard in our G-MEXCLP model. For example, if there is one time standard, and if all demand points are required to be covered at least once, the minimum number of ambulances can be decided by solving the LSCP model (Toregas et al., 1971). But, in our case, it is difficult to determine the minimum number of ambulances. Nevertheless, the solutions of the LSCP model with different time standards are given in the model implementation section. Therefore, different P values, number of available ambulances, are used in the computational studies.

As expected, there is a strong relationship between the number of ambulances (P) and busy fraction (q). We can calculate the busy fraction (q) value according to the following formula below after determining the initial value for P (Marianov and ReVelle, 1996):

$$q = \frac{\bar{t} \sum_i d_i}{24P}$$

where,

$\bar{t}$ = Average duration of a single call, in hours,

d_i = Total demand of demand point i per day,

P = Number of available ambulances.

It is assumed that $\bar{t}$ value is calculated as defined below:

$\bar{t}$ = Average ambulance setup time + Average travel time from station to the incident scene + Time spent at the scene + Probability of delivery to hospital * (Average travel time from scene to hospital + Average time spent at hospital + Average travel time from hospital to station) + Probability of no delivery to hospital * Average travel time from scene back to station.

These average values are set as follows:

$\bar{t}$ = 2 + 7 + 10 + 0.34 * (7 + 5 + 7) + 0.66 * 7 = 30.08 min

$\sum_i d_i$= 12,152 calls /month, $\sum_i d_i$= 405.0667 calls /day

$$q = \frac{30.08/60 \text{ hours} * 405.0667 \text{ calls/day}}{24 \text{ hours/day} * P}$$

According to this formula, q values are calculated for different P values. These values are shown in Table 4.1.

Table 4.1. Busy Fraction Values for Several Values of P for the Test Data

P (total number of ambulances)	q (busy fraction of ambulances)	P (total number of ambulances)	q (busy fraction of ambulances)
10	0.85	21	0.40
11	0.77	22	0.38
12	0.71	23	0.37
13	0.65	24	0.35
14	0.60	25	0.34
15	0.56	26	0.33
16	0.53	27	0.31
17	0.50	28	0.30
18	0.47	29	0.29
19	0.45	30	0.28
20	0.42		

4.2.1.3. Model Implementation

Computational studies are implemented using Optimization Software, and Excel is used to obtain the parameters of the mathematical model. The model is coded in The General Algebraic Modeling System (GAMS) that utilizes CPLEX solver. This code is presented in Appendix A. It is run on ASUS Intel Core i7-4500U CPU @ 1.8 GHz 2.4 GHz.

The first results of the model for the stated parameters are listed in Table 4.2. According to these results, 10 and 11 ambulances cannot satisfy the constraints of the model, and the minimum number of ambulances satisfying the constraints of the model is 12. Thus, this result with 12 ambulances shows that 90.77% of total demand can be covered once in 6 min, 69.39% of total demand can be covered twice in 9 min, and 63.50% of total demand can be covered three times in 12 min. Moreover, all of the demand is covered at least once under these conditions, with the minimum feasible number of ambulances.

As stated in the previous section, if all demand points are required to be covered at least once in a specific time standard, the minimum feasible number of ambulances can be decided by solving the LSCP model (Toregas et al., 1971). Otherwise, a feasible solution for the number of ambulances cannot be obtained. However, it is difficult to determine the minimum number of ambulances that satisfy constraint (4), since this constraint forces to cover all of the demand points at least at one of these coverage levels each of which has a different time standard. Therefore, LSCP model is solved for each of these time standards with the test data, and the following results are obtained:

The minimum number of ambulances to cover all demand nodes at least once in 6 minutes is 16.

The minimum number of ambulances to cover all demand nodes at least two times in 9 minutes is 17.

Table 4.2. G-MEXCLP Model Results for Different P Values

Scenario	Total # of Amb's (P)	Busy Fraction (q)	α_1, α_2, α_3	LP Objective	MIP Objective	MIP Gap	Solution Time (sec)	Ambulance Location Nodes	% of Demand Covered				
									(k =1)	(k =2)	(k =3)	(k =4)	(k =5)
1.1	10	0.84	0.00	Infeasible	Infeasible								
1.2	11	0.77	0.00	Infeasible	Infeasible								
1.3	12	0.7	0.00	8039.82	7324.33	9.8	16894.49	13,54,85,107,148,161,171,199, 228,256,301,322	90.77%	69.39%	63.50%	71.30%	25.00%
1.4	13	0.65	0.00	8897.85	8804.03	1.1	63907.56	13,38,52,62,84,107,151,161,191, 236,278,289,322	93.37%	82.93%	73.39%	75.24%	45.13%
1.5	14	0.6	0.00	9944.22	9845.76	1.0	53916.75	30,34,42,43,58,86,107,141,161, 187,202,236,274,294	97.12%	87.25%	80.34%	77.75%	56.84%
1.6	15	0.56	0.00	10661.88	10565.28	0.9	4159.06	24,30,42,58,78,99,115,141,161, 187,202,236,266,294,322	98.90%	91.94%	81.20%	86.55%	66.58%
1.7	16	0.53	0.00	11138.16	11027.97	1.0	748.61	30,36,50,59,62,82,99,115,131, 141,190,236,269,284,294,322	99.42%	95.18%	85.93%	91.29%	69.58%
1.8	17	0.5	0.00	11506.61	11392.72	1.0	144.22	29,34,42,59,80,93,116,131,138, 164,180,210,236,258,277,302,322	99.88%	98.99%	87.96%	92.66%	72.84%
1.9	18	0.47	0.00	11766.34	11655.95	0.9	85.11	10,36,42,46,59,74,99,116,131,141, 170,180,224,239,256,278,303,321	99.88%	98.77%	95.91%	93.49%	77.63%

The minimum number of ambulances to cover all demand nodes at least three times in 12 minutes is 19.

G-MEXCLP model is able to cover all demand at least in one of these coverage levels by using only 12 ambulances. This shows that G-MEXCLP model saves at least 3 ambulances; moreover, 7 ambulances in the third case. Therefore, it is very advantageous to use the gradual coverage model with more than one level instead of using a model covering with a single level coverage only in terms of the number of ambulances.

The results of the model are highly sensitive to t_k values. For example, the reason of increasing coverage for k=4 is that t_4 value is determined as high with respect to the data structure. These results show that lots of demand nodes can easily be covered for this coverage level. Therefore, G-MEXCLP model might not give such a result for another data set (see Table 4.4).

Moreover, G-MEXCLP model favors the nodes with higher demand by utilizing the demand of each node (d_i) used as a weight in the objective function. G-MEXCLP model tries to cover these in as many as possible levels starting with the first level by locating available ambulances in suitable places. Nevertheless, the nodes with lower demands are not discarded due to the mandatory coverage constraint (4). As an example, the ambulance allocation plan of scenario 1.3 is given in Figure 4.6 (Ambulances are represented with triangular shapes).

The list of demand in descending order is given in Table B.1 in Appendix B. According to the results of scenario 1.3, the nodes that have high demand such as 51, 14, 54, 27, 72, 75 are covered in 5 different levels, while the nodes with lower demand such as 237, 238, 240, 241, 242, 319 are covered only in one of the levels. In addition, all y_{ik} values for this scenario are given in Table C.1. in Appendix C.

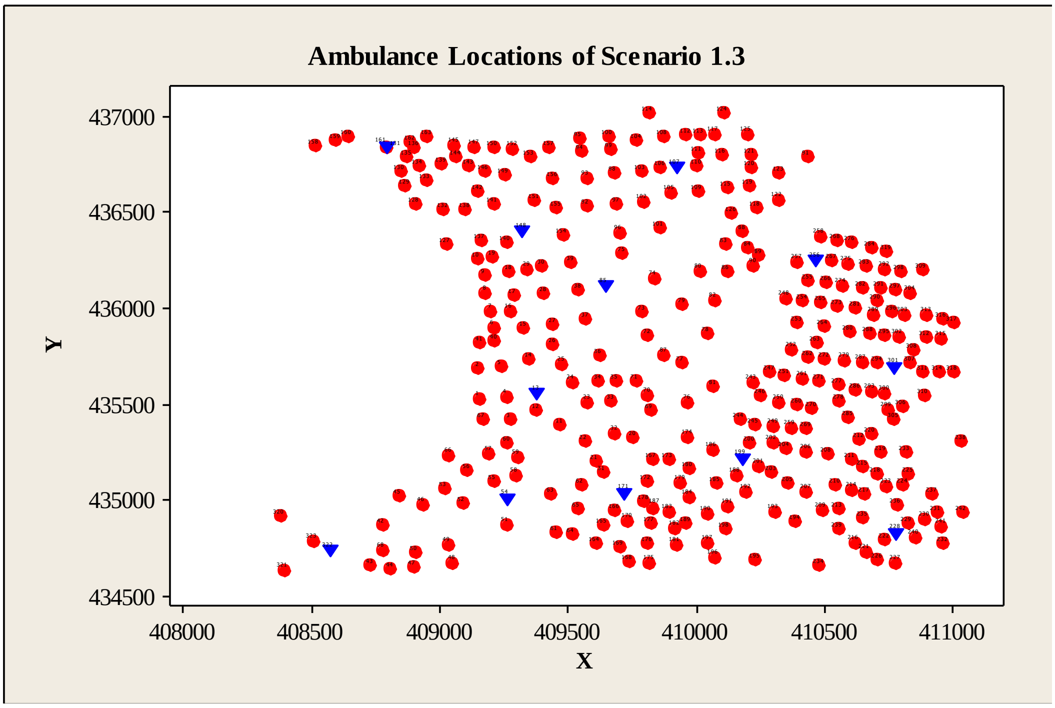

Figure 4.6. Ambulance Allocation of Scenario 1.3

It is expected that the percent of demand coverage is improved as the total number of available ambulances is increased. There is an increase in the percent of demand coverage monotonically as the number of ambulances for each level is increased. As it can be seen in Figure 4.7, the percent coverage increases when total number of ambulances is increased. This is an indicator for the validity of G-MEXCLP.

The demand of each node 139 and 236 is increased to 10,000 in order to test the behavior of the model under various conditions; and scenario 1.4 is resolved with this new demand. Ambulance location of the original scenario 1.4 is seen on the map in Figure 4.8.

On the other hand, ambulance location of the scenario 1.4 after the demand of node 139 and 236 (black rectangles in Figure 4.9) is increased to 10,000 is seen in Figure 4.9.

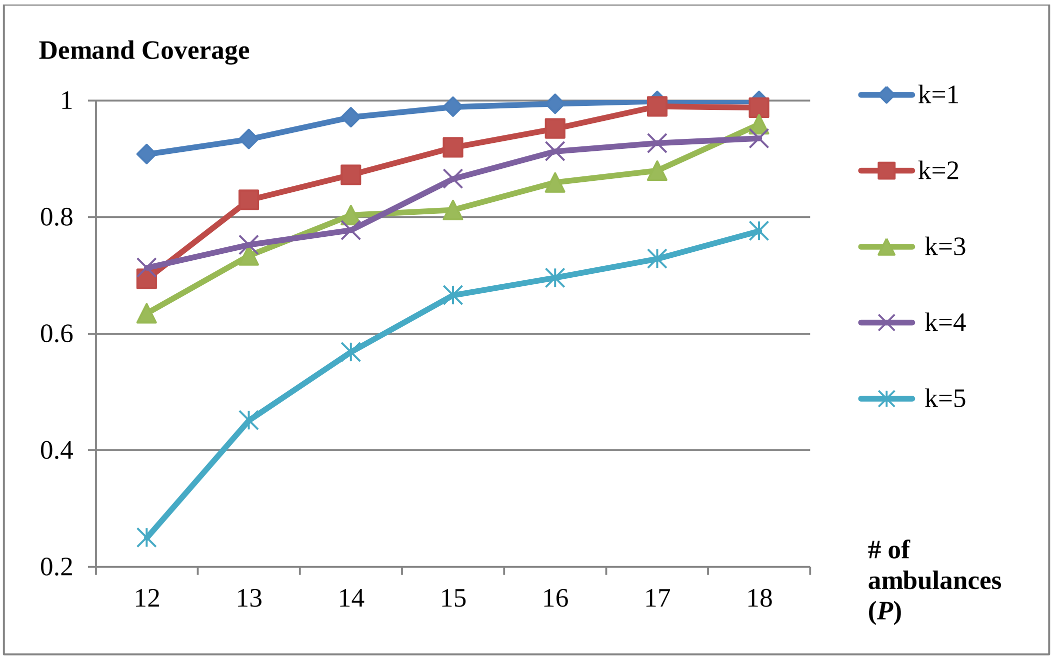

Figure 4.7. Number of Ambulances vs. Demand Coverage

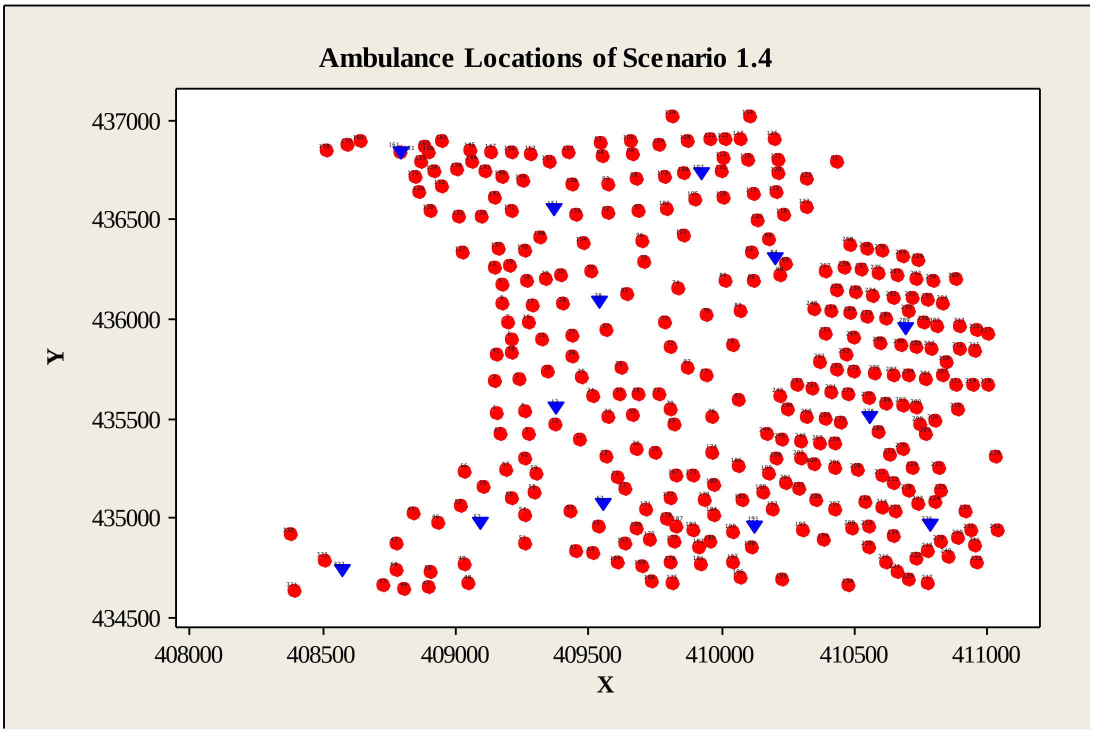

Figure 4.8. Ambulance Locations of Scenario 1.4

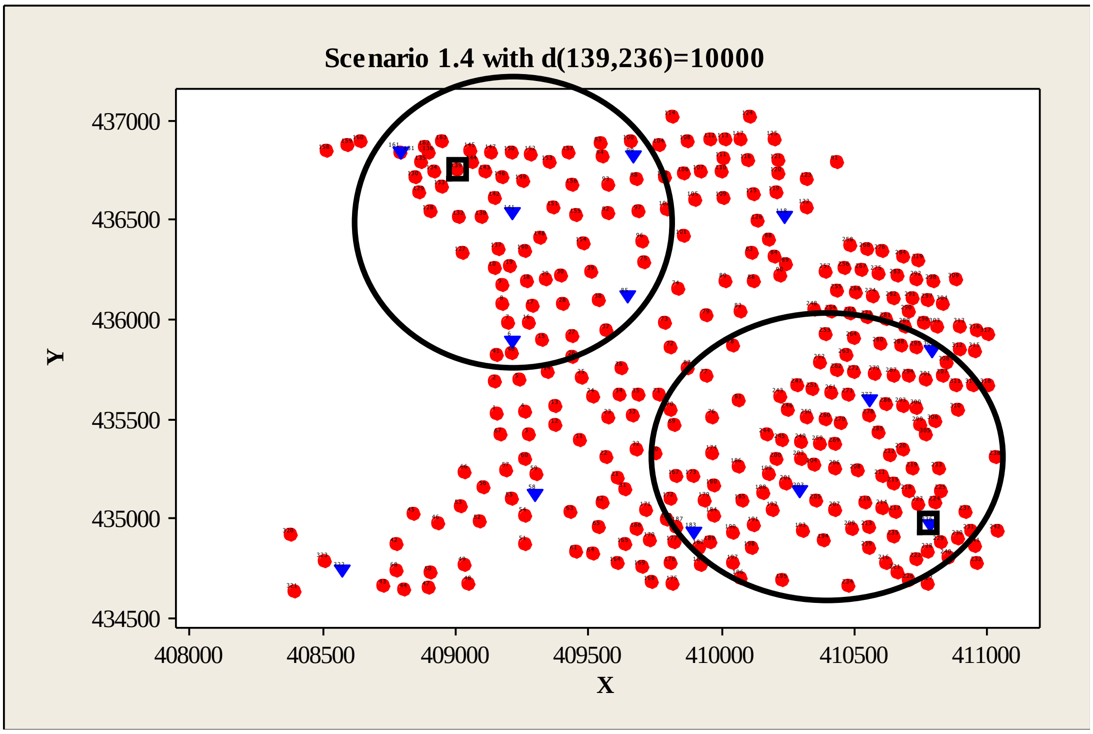

Figure 4.9. Ambulance Locations of G-MEXCLP Model with Extreme Demand

According to these two maps, G-MEXCLP model places 5 ambulances around the nodes that have higher demand to try to cover at all levels. So, the decision variable, y_{ik} takes value for all k for these nodes. Due to the specified t_k values, 5 ambulances are located around the nodes 139 and 236 from the shorter diameter to the larger one. Thus, the other demand points are not neglected. This shows that it is important to determine these t_k values according to the decision maker's requirements.

For example, if t_k values are determined as 6, 8, 10, 12, 14 or as shorter interval such as 6, 7, 8, 9, 10, respectively for k=1,2,3,4,5, these 5 ambulances are located close to these demand points (139 and 236). However, G-MEXCLP model gives importance to other demands points more than the other modeling approaches that have one time standard only. For example, MEXCLP model is solved with 6 minutes time standard, and it is observed that it covers the nodes with high demand disregarding almost all the other demand points (see Figure 4.10).

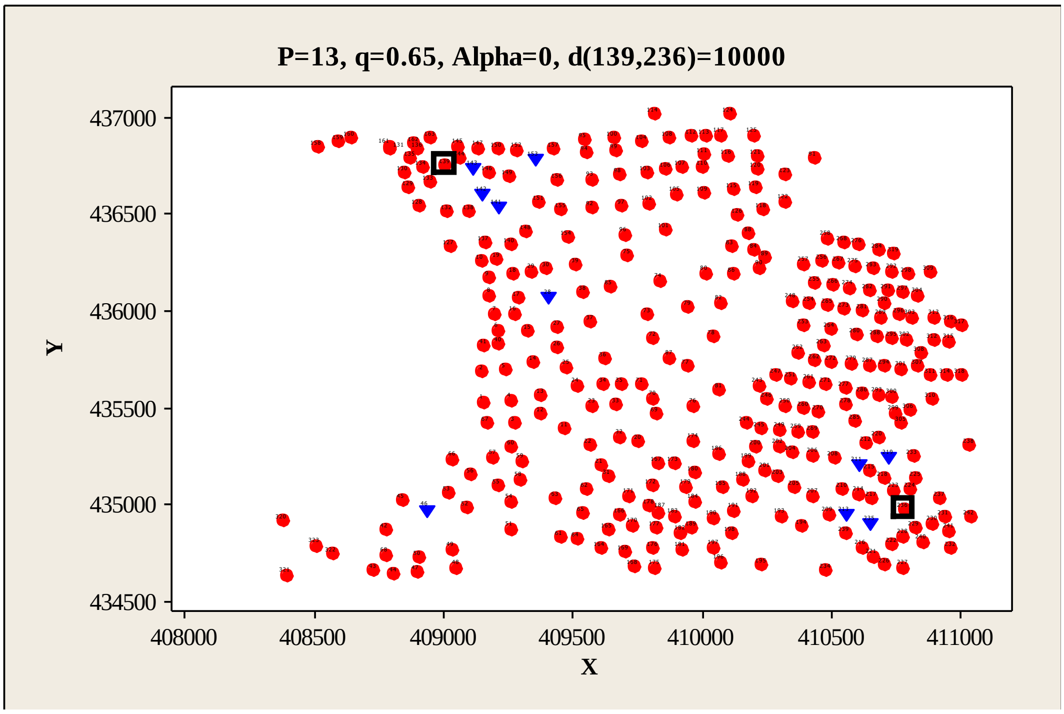

Figure 4.10. Ambulance Locations of MEXCLP Model with Extreme Demand

4.2.2. Computational Results for the City of Adana

4.2.2.1. Data

G-MEXCLP model is also tested with the data for the city of Adana obtained from the master thesis study by Coşkun (2007). Data includes 65 aggregated demand points, the average travel times between demand points, and the population of each demand point (see Table B.2 in Appendix B). Travel time information is directly used in the studies, and the average demand information of each point is inferred from the population. The monthly demand of each node is presented in Table B.3 in Appendix B.

4.2.2.2. Initial Values of the Parameters

When G-MEXCLP model is solved using the data for the city of Adana, coverage levels, k, are set as k=1,2,…5 as in the test data, and t_k values are determined as t_1=6 min, t_2=7 min, t_3=8 min, t_4=9 min, and t_5=10 min for this problem. The parameter, a_{ijk}, is used in the model according to these t_k values for each k. k' value is again set as 3 for this problem. Demand data obtained from the population information are directly used as the demands of nodes.

α_k values are assumed to be zero initially and the model is run to see the percentage of covered demand at each level. Afterwards, some values are assigned to α_k as needed.

The computational studies are conducted for different numbers of ambulances (P) with the data for the city of Adana as well.

The busy fraction value for this data is estimated by using the same formula (Marianov and ReVelle, 1996) as in the test data.

All the values in the formula are the same as in the test problems except the demand per day. The demand is calculated from the population information of the original data as stated at the beginning of this section:

$\bar{t}$ = 30.08 min

$\sum_i d_i$= 12,262 calls /month, $\sum_i d_i$= 408.7333 calls /day

$$q = \frac{30.08/60 \text{ hours } * 408.7333 \text{ calls/day}}{24 \text{ hours/day} * P}$$

According to this formula, q values are calculated for different P values for this data. These values are shown in Table 4.3.

4.1.1.1. Model Implementation

The first results of the model for the stated parameters are listed in Table 4.4. According to these results, a feasible solution cannot be obtained by 10 ambulances, and the minimum feasible number of ambulances turns out to be 11. It means that, 80% of total demand can be covered once in 6 min, 75% of total demand can be

Table 4.3. Busy Fraction Values for Different Values of *P* for the City of Adana

P (total number of ambulances)	*q* (busy fraction of ambulances)	*P* (total number of ambulances)	*q* (busy fraction of ambulances)
10	0.85	20	0.43
11	0.77	21	0.41
12	0.71	22	0.39
13	0.66	23	0.37
14	0.61	24	0.36
15	0.57	25	0.34
16	0.53	26	0.33
17	0.50	27	0.32
18	0.47	28	0.30
19	0.45	29	0.29
20	0.43	30	0.28

covered twice in 7 min, and 72% of total demand can be covered three times in 8 min. Moreover, all of the demand is covered at least once under these conditions. LSCP (Toregas et al., 1971) model is solved for each of these time standards (for each of these levels) for Adana as well, and the following results are obtained.

The minimum number of ambulances to cover all demand nodes at least once in 6 minutes is 15.

The minimum number of ambulances to cover all demand nodes at least two times in 9 minutes is 17.

The minimum number of ambulances to cover all demand nodes at least three times in 12 minutes is 15.

G-MEXCLP model is able to cover all demand at least one of these coverage levels by using only 11 ambulances. This shows that G-MEXCLP model saves at least 4 ambulances; moreover, 6 ambulances in the second case. Therefore, it is very advantageous to use the gradual coverage model with more than one level instead of using a model covering with a single level coverage only in terms of the number of ambulances.

Table 4.4. G-MEXCLP Model Results for Different P Values for Adana Case

Scenario	Total # of Amb's (P)	Busy Fraction (q)	α_1, α_2, α_3	MIP Objective	Solution Time (sec)	Ambulance Location Nodes	% of Demand Covered				
							(k =1)	(k =2)	(k =3)	(k =4)	(k =5)
2.1	10	0.85	0.00	Infeasible							
2.2	11	0.78	0.00	6223.41	50.17	11,15,16,25(2),31,39,41,53,57,62	80.17%	74.95%	71.63%	55.52%	59.81%
2.3	12	0.71	0.00	8278.48	14.06	5,11,15,17,23,27,31,35,51,53,57,62	96.36%	82.44%	71.06%	64.31%	75.04%
2.4	13	0.66	0.00	9385.29	11.25	5,8,11,15,17,23,27,31,35,51,53,57,62	96.36%	85.69%	78.07%	77.02%	84.59%
2.5	14	0.61	0.00	10265.66	14.59	5,12,15,17,20,23,27,31,34,36,51,53,57,62	97.76%	90.14%	86.75%	79.00%	84.59%
2.6	15	0.57	0.00	10891.87	8.59	5,7,11,15,17,23,27,30,34,36,51,52,57,61,62	97.33%	94.02%	89.81%	90.47%	92.03%
2.7	16	0.53	0.00	11343.88	3.77	5,12,15,17,20,23,27,30,31,34,36,51,57,59,61,62	98.73%	95.34%	95.78%	90.08%	92.03%

Scenario 2.2 is solved again with the parameter, α_1=0.90, to show how constraint (3) of the model works, and why it is used. The reason of adding this parameter as 0.90 is that the total covered demand at the first level is 80%, and it is considered as unsatisfactory. So, the model is restricted to cover more demand at level k=1, and the results are obtained as in Table 4.5.

According to these results, it is observed that percent of covered demand at higher levels decreases in order to increase the percent of covered demand at the first level (k=1). This feature of G-MEXCLP model provides flexibility to the decision maker in order to cover the demand points at the desired level. However, total number of ambulances may not be sufficient to meet the desired coverage. For example, if α_1 is set to 0.95 instead of 0.90 in scenario 2.8, the model gives an infeasible result. One of the reasons of this situation is that there is a minimum number of ambulances to meet some conditions, and the other reason is constraint (4), i.e., a demand point should be covered at least once at the first three levels. This constraint is added to the model to consider all the demand points. If a decision maker gives importance to the coverage of a specific level, the model can be solved by adding the corresponding α_k to the model; if the available number of ambulances does not meet this request, the model might be solved by omitting constraint (4). As an example, scenario 2.8 is solved by using the parameter, α_1, as 0.95, and omitting constraint (4). The results are obtained as in the scenario 2.9 in Table 4.6.

The percent of covered demand at the first level (k=1) increases by omitting constraint (4). According to these results, different values might be given to the parameters, α_k, by taking the decision maker's request, and the available number of ambulances into consideration.

As in the test data, G-MEXCLP model tries to cover the higher demand points in as many levels as possible starting with the first level while covering the lower demand points in at least one of the first three levels. For example, according to the results of scenario 2.2, the nodes that have high demand, such as 42, 41, 43, 9, 22, are covered in 4 or 5 different levels, while the nodes with lower demand, such as 18, 10, 65, 64, 15, 49, are covered only in one of the levels. A list of the demand in descending

Table 4.5. G-MEXCLP Model Results for α_1 = 0.90

Scenario	Total # of Amb's (P)	Busy Fraction (q)	α_1	α_2, α_3	MIP Objective	Solution Time (sec)	Ambulance Location Nodes	% of Demand Covered				
								(k =1)	(k =2)	(k =3)	(k =4)	(k =5)
2.2	11	0.78	0.00	0.00	6223.41	50.17	11,15,16,25(2),31,39,41,53,57,62	80.17%	74.95%	71.63%	55.52%	59.81%
2.8	11	0.78	0.90	0.00	6082.38	18.53	5,11,15,17,23,27,35,41,53,57,62	91.89%	64.74%	55.98%	57.58%	58.64%

Table 4.6. G-MEXCLP Model Results for α_1 = 0.90 and 0.95

Scenario	Total # of Amb's (P)	Busy Fraction (q)	α_1	α_2, α_3	MIP Objective	Solution Time (sec)	Ambulance Location Nodes	% of Demand Covered				
								(k =1)	(k =2)	(k =3)	(k =4)	(k =5)
2.2	11	0.78	0.00	0.00	6223.41	50.17	11,15,16,25(2),31,39,41,53,57,62	80.17%	74.95%	71.63%	55.52%	59.81%
2.8	11	0.78	0.90	0.00	6082.38	18.53	5,11,15,17,23,27,35,41,53,57,62	91.89%	64.74%	55.98%	57.58%	58.64%
2.9	11	0.78	0.95	0.00	6656.34	9.30	8,12,15,23,27,33,35,41,52,57,61	95.03%	64.81%	64.95%	68.46%	78.77%

order is given in Table B.3 in Appendix B, and all y_{ik} values obtained from this scenario are given in the Table C.2 in Appendix C.

As it can be seen in Figure 4.11, the percent of coverage increases as the total number of ambulances increases for this data set, too.

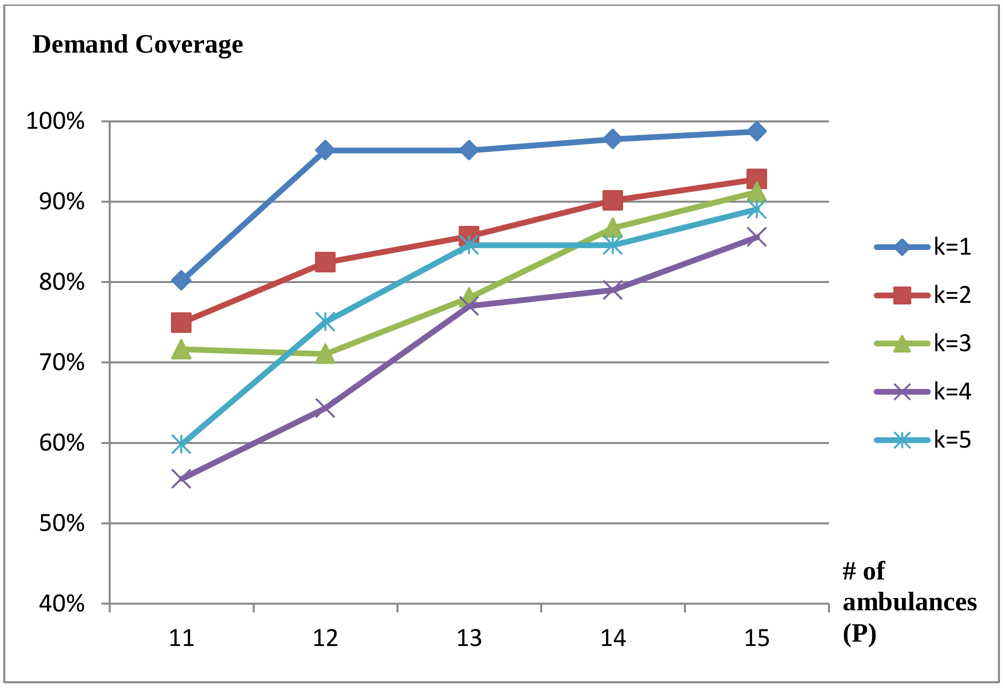

Figure 4.11. Number of Ambulances vs. Demand Coverage for Adana Case

As it can be seen in Table 4.7, the coverage for larger k values increases when the busy fraction is increased.

As a result of the solutions obtained with G-MEXCLP model, we can be confident that G-MEXCLP model coded in GAMS is valid in terms of finding suitable locations for the ambulances.

The following chapter presents the simulation model that we develop to observe the results of the G-MEXCLP model in a stochastic environment.

Table 4.7. G-MEXCLP Results for Increasing Busy Fraction for Adana Case

Scenario	Total # of Amb's (P)	Busy Fraction (q)	α_1	MIP Objective	Solution Time (sec)	Ambulance Location Nodes	% of Demand Covered				
							(k =1)	(k =2)	(k =3)	(k =4)	(k =5)
3.1	11	0.4	0.00	9700.79	13.38	5,11,15,17,23,27,35,41,53,57,62	91.89%	64.74%	55.98%	57.58%	58.64%
3.1	11	0.6	0.00	8404.40	16.86	5,11,15,17,22,27,35,41,53,57,62	88.83%	70.68%	62.08%	52.03%	50.37%
3.1	11	0.78	0.00	6223.41	50.17	11,15,16,25(2),31,39,41,53,57,62	80.17%	74.95%	71.63%	55.52%	59.81%

CHAPTER 5

SIMULATION MODELLING

5.1. Motivation for Simulation Modeling

Using computer simulation for optimization is a favorable practice for its convenience and economic advantages when compared to empirical research or real world testing. Simulation provides a means to model the real world systems and perform experiments as needed on this once modeled media.

In EMS services, as suggested before, quality of the medical service as well as quick responses to emergency calls are of vital importance (Sanchez-Mangas et. al, 2010). On the other hand, expenditure for healthcare is increasing worldwide as the studies show (Aboueljinane et al, 2013), meaning that resource management in healthcare will become even more important in the future. For these reasons, computer simulation is a useful tool for both improving the quality of the emergency medical service and optimization of utilization of resources, providing testing of models, planning and strategic decision making at low cost with high flexibility.

Even a basic simulation model can reveal many interesting points about a real world problem that may not be found otherwise without experiencing the real phenomena, and the outcome in the realm of EMS may be to find out the performance and bottlenecks of different EMS management systems, models and strategies. This valuable information may otherwise come from practical experience that may result in inefficient usage of resources or even loss of human lives in EMS systems.

Moreover, the natural flow of the EMS service routine fits well into simulation environment, and can be modeled with relative ease. Statistical information that can be gained in such simulation experiments such as average response times to an emergency call is of great importance for making strategic decisions and building mathematical models for location and relocation of ambulances, and systematic improvement of EMS systems. Moreover, statistics that can only be estimated in the mathematical models can be obtained by using the simulation models besides the statistics whose real values cannot be obtained by using mathematical models such as response time and average waiting time in queue of the emergency calls.

For these reasons, a simulation model is built to be able to test the results of the mathematical model, G-MEXCLP, against the simulation environment to observe the behavior and performance of the G-MEXCLP model. The result of this investigation will be utilized to improve G-MEXCLP model systematically as presented in our solution approach in the following chapter.

This chapter continues with the details of the simulation model.

5.2. Overview of the Simulation Model

In this part, a general overview of the simulation model we have developed is presented along with the rationale regarding considerations made during the development of the simulation model.

Simulation model is built on Rockwell Automation's Arena® (Version 14.7) discrete-event simulation and automation software. Arena uses SIMAN processor and simulation language. In Arena, flow of events can be modeled through *modules* (boxes for different functionalities, logic or processes) connected to other modules. *Entities* flowing along these modules according to the defined logic, processes, and timings constitute the simulation. User can get statistical data, placing specific modules providing recording abilities and also get detailed reports of desired information from the simulation. The working principles of the simulation are presented in detail in the following sections.

Simulation model is developed, and tested; and run is made at a computer with Intel Core i7-4770S CPU @ 3.10 GHz with 16 GB RAM.

5.2.1. Basic EMS Process

In order to establish a valid simulation model, it is important to build upon real EMS service process. A flowchart of EMS service is shown in Figure 5.1 summarizing the basic EMS process. The simulation model is built upon this flowchart integrating necessary details, mechanisms, and metrics.

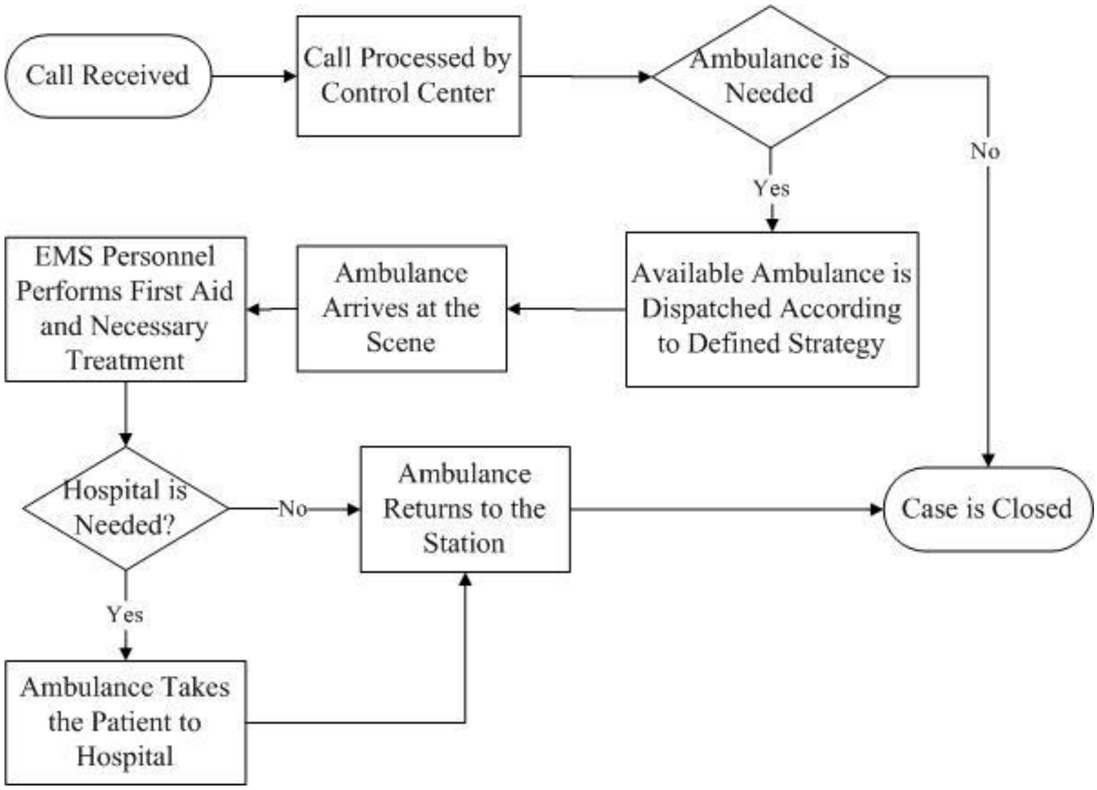

Figure 5.1. Basic EMS Process

5.2.2. Terms and Definitions of the Simulation Model

A list of definitions and terms are described below before we go into details of the simulation model.

- *Modules* are boxes for different functionalities, logic or processes in Arena. The simulation model consists of interconnected modules.

- The emergency call is accepted as the main *entity*, and the system is built upon the journey of the *call* throughout the simulation system. In other words, the call is processed through the modules of the simulation model and all the logic and processes are performed on this *entity* named *call*.

- *Locations* are defined as the different districts of the area that the emergency service authority serves, and where the ambulances are placed.

- Ambulances are distributed among *stations* (locations where ambulances reside) according to the results provided by G-MEXCLP model, which is an input to the simulation model, prior to simulation start.

- A *dispatch* is defined as the departure of an ambulance from a station to go to an emergency event scene (*location* of the *call*).

5.2.3. Assumptions

A number of assumptions are made in order to deal with the complexity of the EMS environment. These are as follows:

- An incoming emergency call is assumed to come from a distinct *location* which is identified by the CC based on the information from the caller by triage or by any other means.

- The distance from each *station* to each *location* is known which is the travel time of an ambulance from each station to each location. This information is an input to simulation prior to simulation start.

- The average travel time in the same location are assumed to be 1 minute. If calls are taken from the location of the ambulance, travel time is taken as 1 minute.

- Geographical information system usage is not considered in the model; therefore, an ambulance is assumed to be available only after it returns to its *station* from a *dispatch*.

- Also *missed dispatches* are not modeled. Missed dispatch is a false alarm when an ambulance dispatches from its station, but the request for an ambulance is cancelled before the ambulance arrives at the scene.

- The incoming calls are interpreted to have two degrees of *emergency type* that is set by the *call center* personnel (*triage*), in other words severity of the case is categorized into two degrees by means of triage, which are severe and not severe.

- If the patient is found to be in need of a treatment at a hospital by the ambulance crew, it is assumed that the patient is taken to the nearest hospital.

5.2.4. Inputs of the Simulation Model

It is intended that the data processed by the simulation model reflect real world cases as much as possible, and hence, some of the assumptions regarding duration of certain events and probability distributions of some of random variables are based on the most common assumptions and real cases in the literature.

Call Arrival Rate

Call arrival rate is the most probabilistic part of the EMS problems. Various techniques can be used to predict this rate such as historical data analysis. Most of the studies using simulation in EMS problems uses Poisson distribution for call arrivals (Goldberg et al., 1990; Borras and Pastor, 2002; Silva and Pinto, 2010, Zhen et al., 2014) or uses exponential distribution for interarrival time between calls (Christie and Levary, 1998; Kozan and Mesken, 2005; Mason et al., 2013). In this study, it is assumed that the interarrival time between calls is exponentially distributed. Calls are created by using the expression, EXPO (μ). Mean value is calculated using the number of total demand (calls) in an hour from the data available. Nevertheless, different mean values can be used in different scenarios.

Spatial Distribution of Calls

Total demand of ambulances from each region is used as an input to the simulation model. Each region has its own demand and therefore there is a total demand for all regions combined. Total demand for each region divided by the total demand of all regions gives the demand for ambulances for each region as a percentage. Discrete distribution is used to utilize this percentage in assigning the call location for an incoming call in the system. The related calculations and expressions are presented in Table 5.1.

Table 5.1. Discrete Distribution for Call Creation

Call Location	% of Demand	Cumulative Probability
Region 1	*a*	*a*
Region 2	*b*	*a*+*b*
Region 3	*c*	*a*+*b*+*c*
…	...	…
Region n	*x*	1.0*

*(*a*+*b*+*c*+…+*x* = 1.0)

This region demand probability is given to the simulation model as an attribute of the call using the following expression:

DISC(a, 1, *a*+*b*, 2, *a*+*b*+*c*, 3,…, 1.0 , *n*)

Control Center Processing Time

After receiving an emergency call, control center processes the call in a time duration which is referred to as control center processing time. In the previous studies, this time duration is represented by a multinomial distribution (Mason, 2015) and lognormal distribution (Kozan and Pastor, 2005). Similarly, in this study, lognormal distribution is used for the time that passes during the assessment of the CC to get information about the location and the emergency level of the call. The expression LOGN (Mean, Variance) is used in the simulation by setting the values of the parameters as (2, 0.5) similar to the studies conducted before (Aringhieri et al., 2007).

Call Type

In this study, it is decided that a differentiation between calls in terms of call type would be unnecessary. This is because of the fact that the G-MEXCLP model does not make this distinction; therefore, it would be inconsistent to do so in the simulation model. Also another fact is that in Turkey, differentiating call type during triage is only made to consider if an ambulance is needed or not, since the triage is not considered to be fully reliable. All calls that need an ambulance are considered to be equally important. Therefore, call type parameter (although actually modeled in the simulation) is not used and all calls are assumed to be of the same type.

Ambulance Need

Ambulance need is one of the information decided upon assessment by the call center during call processing case in which a call does not need an ambulance will be dissolved by the call center and would not be processed any further. Since the demand data we utilize to run our mathematical model, G-MEXCLP, consists of only the cases where an ambulance is sent, it is decided that in the simulation study all calls are ambulance needing calls. Nevertheless, in order to make it possible for further work to simulate such cases, the ambulance need is modeled in the simulation, with a probability of 1 (100%), represented by an attribute which can be adjustable to other percentages if needed.

Ambulances and Their Location

Number of ambulances and their locations are the most important part of the simulation study. The number of available ambulances is also used in the mathematical model as the parameter, P. The same value is used in the simulation. On the other hand, the assignment of ambulances among nodes (stations) is a direct result of the mathematical model, and inputted to the simulation model in matrix form that is read from an excel file. Therefore, it is assumed that the total number of ambulances and their assignment to stations are known prior to the simulation run and are inputs to the simulation.

Ambulance Dispatching

The mathematical model aims to cover demand points at the least possible response time, and while striving for this, as many ambulances as possible are located at the nearest possible location of the demand points. Therefore, in the simulation model, a demand point should be served by as many ambulances as in the mathematical model solution. For this reason, in the simulation model, no region constraint is imposed and a nearest possible available ambulance is assigned for an incoming call. Besides, many existing works in the literature utilizes the nearest available ambulance algorithms in EMS simulations (Aboueljinane et al., 2013).

Ambulance Setup Time

After processing of the call by the control center, a suitable ambulance is directed to the emergency scene according to the dispatching rule defined in the previous section. However, before the ambulance and crew leave their station, some time is needed to load the ambulance with the equipment that may be needed for the case and for the preparation of the crew. Actually, this time is obviously dependent on the emergency call type, because there may be equipment and materials specific to the case although there are some default equipment and materials in the ambulance. However, since the call type is considered to be the same for all calls in this study, so are the distributions for all calls. In the previous studies, it is assumed that lognormal distribution (Kozan and Pastor, 2005), gamma distribution (Repede and Bernardo, 1994) and negative exponential distribution (Zhen et al., 2014) are all suitable for the ambulance setup or pre-trip delay. In this study, lognormal distribution is used to fit for this input. The expression LOGN (Mean, Variance) is used in the simulation by setting the values of the parameters as LOGN(2,0.5), similar to the previous studies in the literature (Ingolfsson et al., 2003).

Travel Time between a Station and a Scene

After ambulance pre-trip preparations, ambulance leaves the station en route to the scene of the event. The duration of this trip is not absolutely fixed as the density situation of the traffic, accidents and similar other factors affect the trip duration substantially. Still, as mentioned in the mathematical model, G-MEXCLP, the distance metric can certainly be used to deduce travel times in the simulation model. However, in order to reflect the randomness of the traffic factors, etc., a better approach may be to use this distance metric as an input variable to some distribution rather than utilizing them as constant values. In the literature, lognormal distribution (Wu and Hwang, 2009; Christie and Levory, 1998) and Gamma distribution (Repede and Bernardo, 1994) are used for the travel time between a station and the incident scene. In this study, lognormal distribution is chosen for this parameter. The expression LOGN (Mean, Variance) is used in the simulation. For the parameter, μ, average time between any two nodes is used as in the mathematical model.

Time Spent at Scene

Once the ambulance arrives at the emergency incident scene, the first aid and other treatment, if required, are conducted on the patient by the ambulance crew which obviously take some time, and this time can be determined by analyzing historical data. However, we prefer to use assumptions commonly made in the studies in the literature. Gamma distribution (Repede and Bernardo, 1994; Lin et al., 2015), Lognormal distribution (Wu and Hwang, 2009), Negative exponential distribution (Zhen et al., 2014), and a constant value (Ingolfsson et al., 2003) are used for the time spent at an emergency scene in the previous studies. It is assumed that Gamma distribution is suitable for on-scene time in our simulation study, and the expression 1+GAMM (α,β) is used.

Hospital Need

The processes mentioned above until a hospital need arises are carried out for each call; however, hospital need exists for only a proportion of the calls. Some of the patients require special or further treatment that may only be conducted at a hospital. On the other hand, some patients get the required treatment by the ambulance personnel; thus, the service terminates at the place of the incident. Hence, the proportion of the cases with a hospital need is of interest for the simulation model. According to Aarytun and Leknes (2014), 43% of the calls end at a hospital, and according to Ingolfsson et al. (2003), 25% of the calls end at a hospital. In this study, it is assumed that 34% of the calls are transported to the hospital. This information is given to the simulation using a discrete distribution, and the expression is DISC (0.34, 1, 1.0, 0). Therefore, "1" represents the calls being transported to a hospital, while "0" means the other calls ending at the incident scene.

Hospital Location

Number of hospitals and their locations are also an input to the simulation. However, this part of the problem is not modeled in the mathematical model, since they are known. Neither the locations of the hospitals nor the locations of the emergency incidents could be changed. Therefore, ambulance service is only responsible for this part of the problem in transporting patients from their location to a hospital if needed. Therefore, in this study, number of hospitals and their locations fulfill a function to ensure integrity and completeness for the simulation study. In order to direct some calls to the hospital, it is assumed that a few hospitals are located at some of the demand nodes. As an example, for the Adana case, hospitals are located in the nodes, 8, 22, 38 and 55 randomly.

Travel Times between Scene and Hospital, and Hospital and Station

For the calls which need to go to a hospital, after some time spent on-scene, ambulance transports the patient to a hospital. The duration of this trip, similar to the case between ambulance station and emergency scene, can be obtained from the distances of nodes as described before. Therefore a similar LOGN (Mean, Variance) distribution is used in the simulation by using the same parameters.

Time Spent at Hospital

At the hospital, carrying the patient to the hospital, transfer of information about the patient and the incident, paperwork, etc. take some time, that can also be obtained by analyzing historical data. Still, in this study, it is chosen to get an idea from the works in the literature in order to determine the time spent at a hospital. Lognormal distribution (Wu and Hwang, 2009), Negative exponential distribution (Zhen et al., 2014), Triangular distribution (Christie and Levory, 1998) and Gamma distribution (Repede and Bernardo, 1994) are used for the time spent at a hospital. It is assumed that triangular distribution is suitable for the time spent at a hospital. The expression 1+GAMM(α, β) is used in the simulation.

5.3. Model Design

Based on the basic flowchart of EMS systems proposed in Figure 5.1 in section 5.2.1, and in the light of the assumptions listed above, a simulation model is built in Arena Ver. 14.7 of Rockwell Automation. In addition to the processes defined in the basic flowchart in Figure 5.1, the simulation model is built such that the statistical properties can be obtained by the simulation (i.e., the performance criteria), and time distributions of events in the process can be included. Simulation model is also intended to be flexible enough, meaning that it can be easily initiated for different ambulance allocations, various time distributions and changing probabilities such as ambulance need, hospital need, etc.

The detailed description of the simulation subsystems are provided in the following sections, and the figures of these subsystems are given. In addition, all attributes and variables that are used in the simulation model are given with their properties and initial values in Appendix F.

5.3.1. Simulation Model Subsystem Descriptions

The structure of the simulation model consisting of a number of subsystems not only simplified the testing and verification of the model, but also made it more comprehensible. Thus, the simulation model consists of five subsystems that are described one by one in the following parts.

Subsystem 1: Call Reception and CC Process

The flow of the modules in Subsystem 1 can be seen in Figure 5.2. The first module of the simulation model is a CREATE block which generates the *entities* of our simulation model, i.e., the *calls*. The expression for this is *EXPO(InterArrivalTime)* as described in above. After that, an attribute called the *StartTime* is assigned at the ASSIGN block. *StartTime* holds the simulation time when a call is received, and for this purpose *TNOW* keyword of SIMAN is utilized.

The fifth block is again an ASSIGN block where the *CallType* attribute is set. As mentioned before, all the calls are assumed to be of the ambulance needing type, therefore, the expression *DISC(pAmbNeeded,1,1.0,0)* ensures that all calls are of Type 1 (ambulance needing). However, if desired, another type of distribution might be selected. Therefore, the DECIDE block labeled *IfAmbNotNeeded* never chooses the upper path, but always chooses the lower part where an ambulance is needed according to the assumptions made.

Continuing on the lower path, the number of calls that need an ambulance is computed at a RECORD block, and after that, there is a PROCESS block labeled *CC Process Delay* which simulates the time that passes during triage of the control

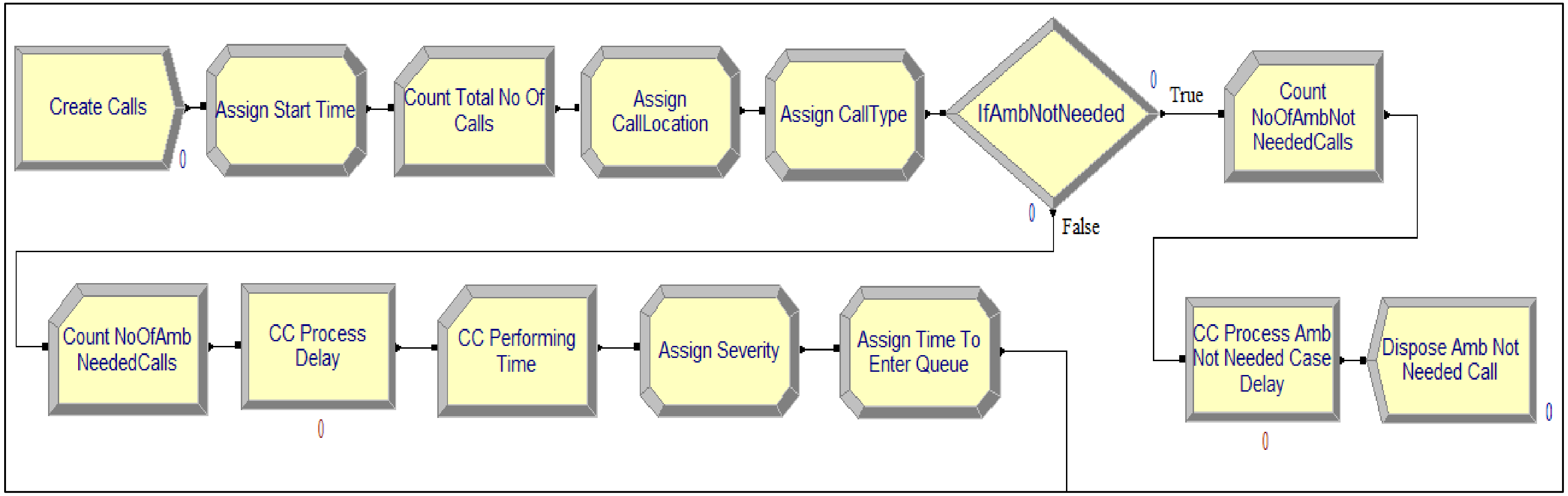

Figure 5.2. Simulation Flow of Subsystem 1

center. The expression for this block is *LOGN(CCPerformingTimeMean, CCPerformingTimeVariance)* and the rationale is described at the related Simulation Inputs part above. The next block in the simulation is labeled as *CC Processing Time* and this RECORD block gets statistics of the realized CC Processing Time, i.e., the duration of the triage. According to this triage, the severity of the call is assigned at the next block, however, once again we do not differentiate any severity between calls and we assign to each call the same severity value. Therefore, this block again is used only to provide means to do so if one desires to take severity into consideration. It is also important to mention here that the *CallQueue* that will be described in Subsystem 2 actually takes severity into account when selecting which call to serve first. However, since we assign always the same severity, it works effectively in a first in first out (FIFO) manner. In this subsystem, the final block is the ASSIGN block that assigns a *TimeToEnterQueue* attribute to each call which is utilized to compute the average waiting time in the queue for a call in the end.

Subsystem 2: Queuing and Dispatch of Ambulance

The flow of the modules in Subsystem 2 can be seen in Figure 5.3. At the end of Subsystem 1, the calls are assigned *TimeToEnterQueue* attributes and all of the incoming calls arrive at a HOLD block labeled *Calls Queue* whose details are shown in Figure 5.4. Therefore, the calls are on hold until there is an available ambulance.

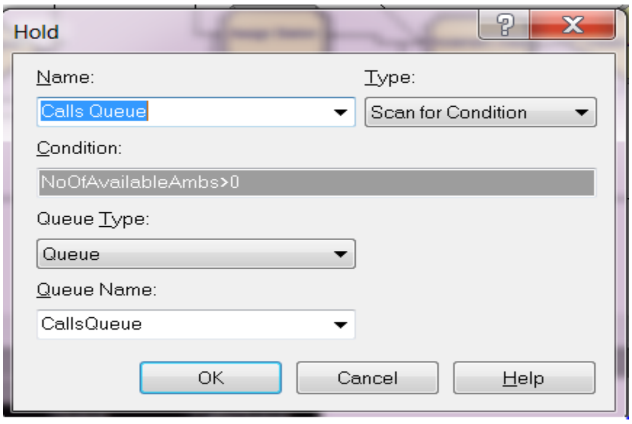

Figure 5.4. Details of HOLD Block-Calls Queue

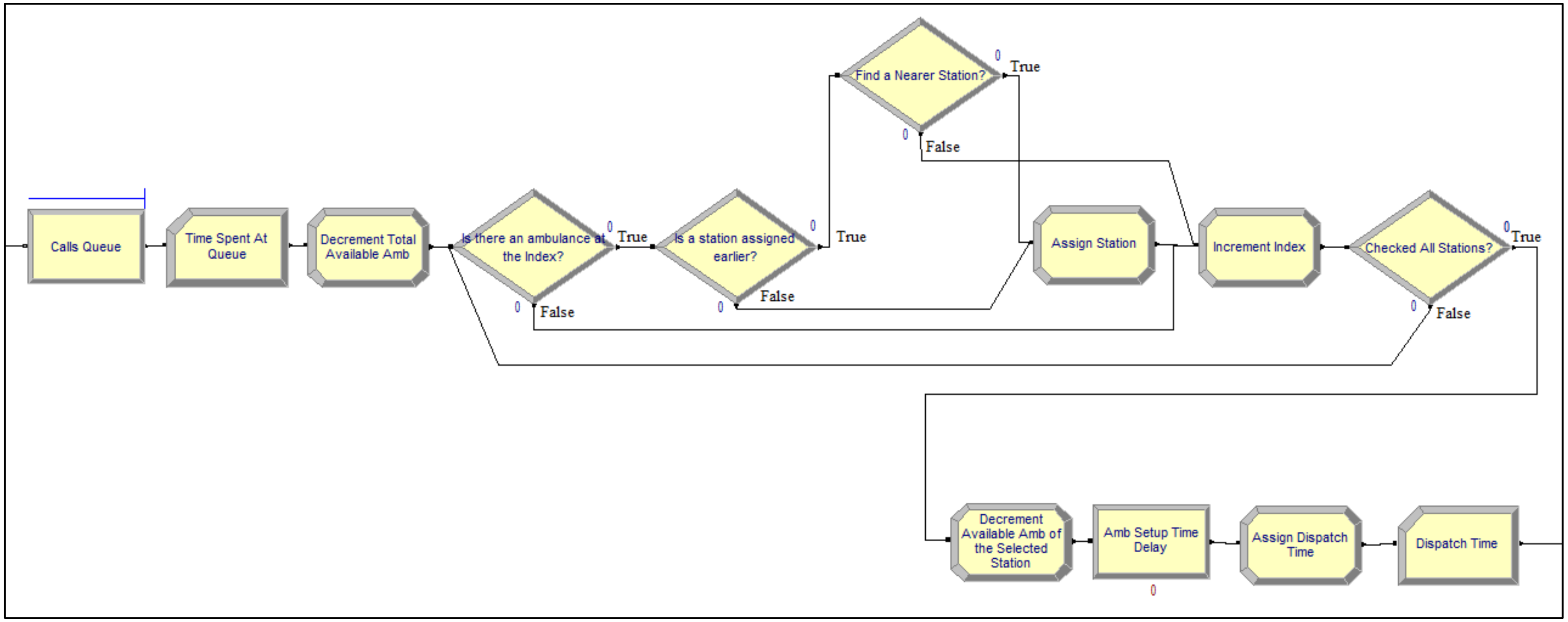

Figure 5.3. Simulation Flow of Subsystem 2

Inside the HOLD block, the calls are put in a queue named *CallsQueue* which releases the highest *Severity* call. Since, in our setting, it is assumed that all calls have the same severity, this QUEUE operates in a FIFO manner (Figure 5.5).

Queue - Basic Process

	Name	Type	Attribute Name	Shared	Report Statistics
1	CallsQueue	Highest Attribute Value	Severity	☐	☑
	Double-click here to add a new row.				

Figure 5.5. Features of Calls Queue

In short, a call waits for an ambulance if there is not any ambulance available to dispacth, and if there are some ambulance available, the calls are released in a FIFO manner. The second block of Subsystem 2 is a RECORD block labelled *Time Spent At Queue* where this value is calculated by the expression *TNOW-TimeToEnterQueue*. The third block is an ASSIGN block to reduce the number of available ambulances by one, since an ambulance is assigned to the current call entity.

The part shown in Figure 5.6, consisting of 6 blocks, is actually a loop to select the nearest possible ambulance among the available ambulances.

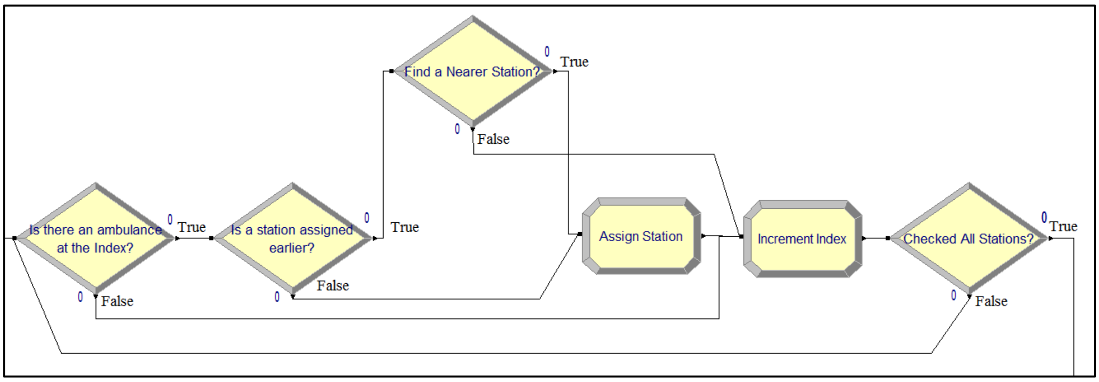

Figure 5.6. Representation of the Simulation Loop to Select an Available Ambulance

At the end of this loop, an attribute named *AssignedStation* holds the index of the station of the ambulance (actually the index of the *AmbMatrix* where the assigned ambulance resides).

Back to Figure 5.3, Subsystem 2 continues with an ASSIGN block where the ambulance count at the *AmbMatrix(AssignedStation,1)* is decreased by one, as it is allocated to the current *call(active entity).* Then a PROCESS block named *Amb Setup Time Delay* simulates the preparation time required for the dispatch of the ambulance. The expression utilized for this purpose is *LOGN(AmbSetupTimeMean, AmbSetupTimeVariance).* The last two blocks of Subsystem 2 calculates (assigns) and records *AmbDispatchTime,* a statistic to hold the time that passes between receipt of a call and an ambulance being ready for dispatch.

Subsystem 3: Ambulance En Route to Scene

At the very start of Subsystem 3, the ambulance is assigned to the call; it is ready for dispatch and begins its trip at Subsystem 3 (Figure 5.7). The first block is a PROCESS block that simulates ambulance travel time from the station of the ambulance to the scene of the emergency. The expression used in the block for this time is set as *logn(TravelTimesMatrix(AssignedStation,CallLocation),0.25*Travel TimesMatrix(AssignedStation,CallLocation)).* After that, since ambulance reaches the scene, in an ASSIGN block, *ResponseTime* is assigned to the value *TNOW-TimeToEnterQueue.* The next block is a RECORD block to get statistical data about *ResponseTime.* The fourth block in the subsystem is an ASSIGN block to populate a *CallCountMatrix* which holds the number of calls from each location. This information is used in the next block for recording average response times calculated for each location separately in a matrix called *ResponseTimeMatrix,* and then for writing to an Excel file in the following READWRITE block. The subsystem continues with a DECIDE block labeled *ResponseTimeCheck* in which the *ResponseTime* of the current entity is checked against a *TargetResponseTime* variable, and if it is less than or equal to the target response time, in the next block a variable named *CoveredDemand* is incremented by one. After that, the Subsystem continues to assign a *Coverage* variable that holds the percentage of *CoveredDemand* over *TotalNoOfCalls.* Along with *ResponseTime* and *BusyFraction, Coverage* is one of the most important performance measures in the simulation model.

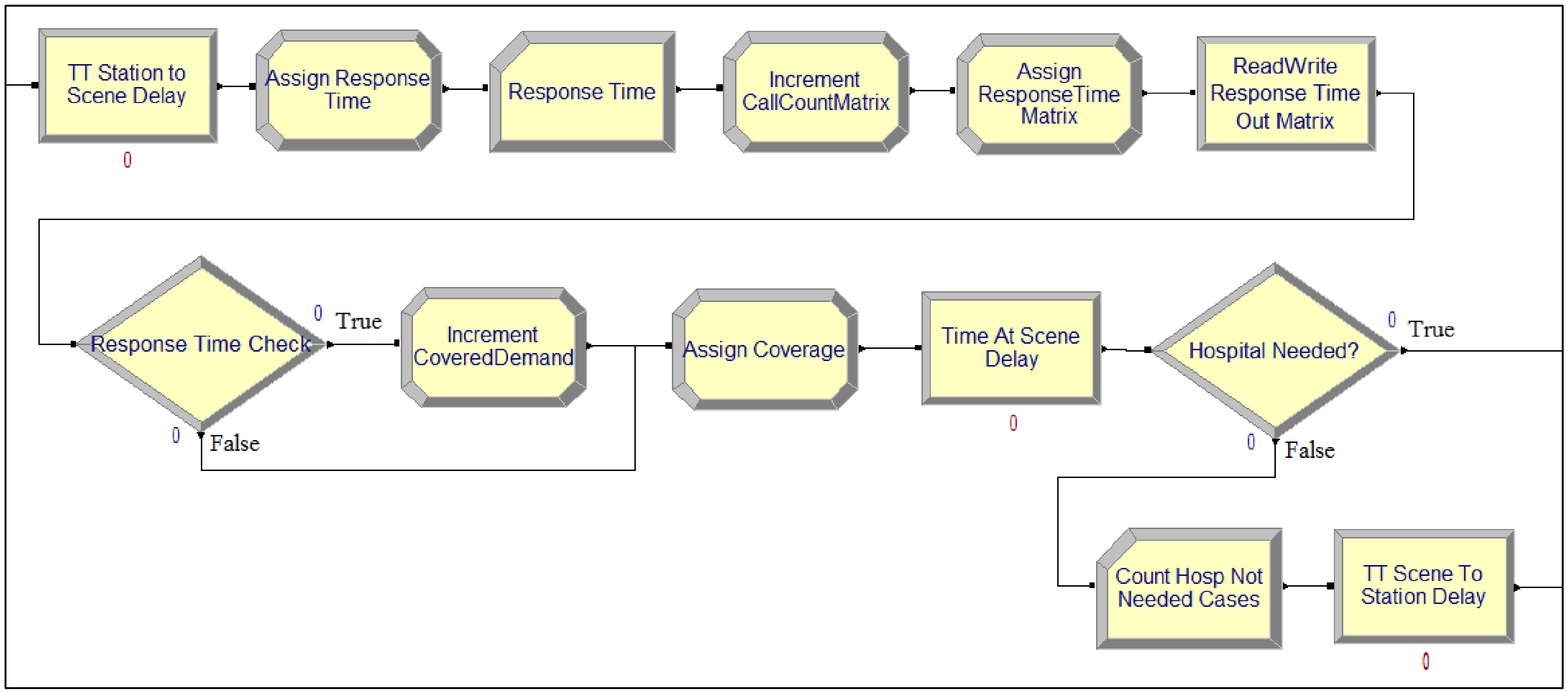

Figure 5.7. Simulation Flow of Subsystem 3

Then the simulation continues at the scene. A PROCESS block simulates the time that passes at the scene during medical treatment by the EMS personnel. The expression for this time is:

TimeAtSceneThreshold + GAMM(TimeAtSceneBeta,TimeAtSceneAlpha).

The DECIDE block labeled *Hospital Needed?* directs the flow to either Subsystem 4 if delivery of the patient to a hospital is needed, or directly to Subsystem 5 if it is not (the upper path). If delivery to a hospital is not needed, this means that the ambulance returns back to the station after departure from the scene. The last two blocks count the cases that do not need delivery to a hospital, and also simulates the time that passes during the trip from the scene back to the station with the expression below:

*Logn(TravelTimesMatrix(CallLocation,AssignedStation),0.25*TravelTimesMatrix (CallLocation,AssignedStation))*

Subsystem 4: Ambulance En Route to Hospital

Subsystem 4 is only run for the cases that need hospital delivery, otherwise the flow continues with Subsystem 5. The flow of Subsystem 4 in seen in Figure 5.8. The first block of Subsystem 4 is an ASSIGN block to set Index attribute back to zero. The *Index* attribute is used only for finding the nearest ambulances and hospitals to a call location. After that, the six blocks form a loop very similar, almost identical, to the one in Subsystem 2. At the end of this loop, the call is assigned to the nearest hospital location, meaning that *AssignedHospital* attribute is given the index of the nearest hospital. The next block is labeled as *TT Scene To Hospital* delay, a PROCESS block to simulate the time that passes in the trip while the patient is taken to the hospital. The expression for this is as follows: *logn(TravelTimesMatrix(CallLocation,AssignedHospital), 0.25*TravelTimesMatrix (CallLocation,AssignedHospital)). Time At Hospital* delay follows it simulating the time that passes at the hospital for paperwork or information exchange, etc. as

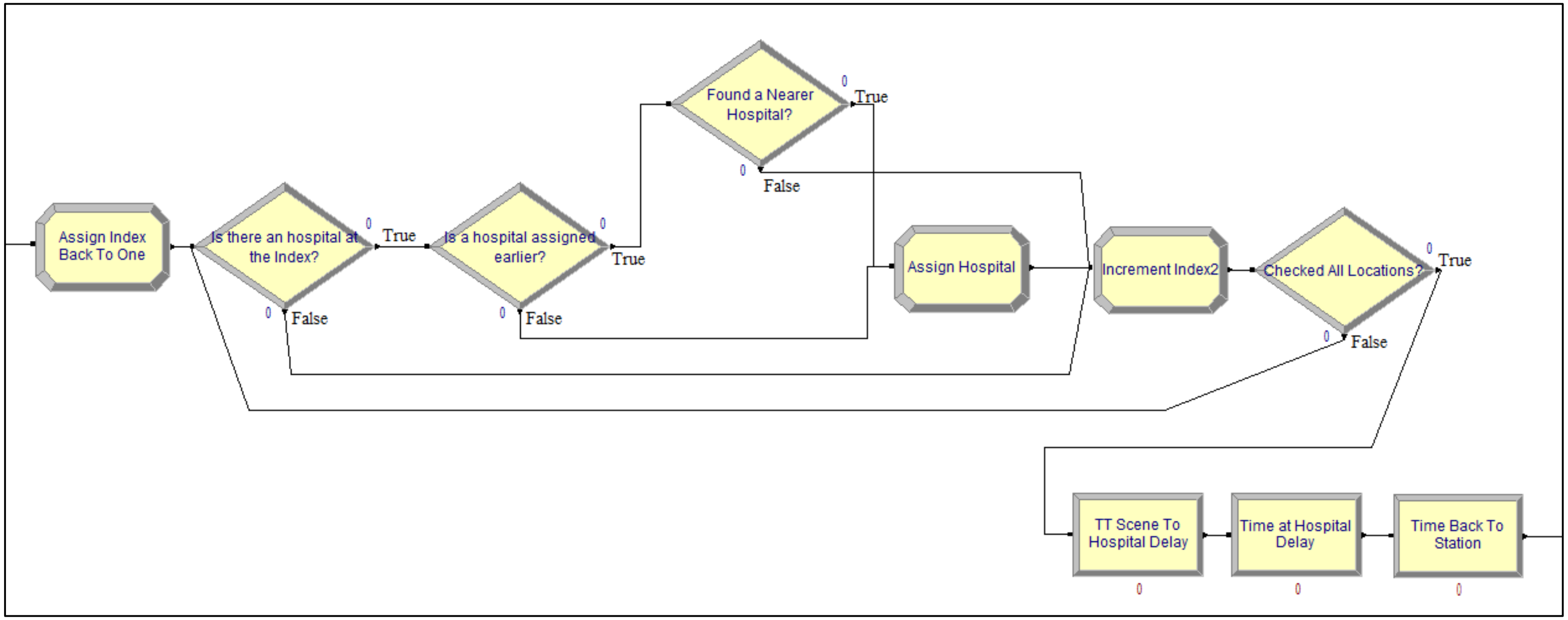

Figure 5.8. Simulation Flow of Subsystem 4

described in the simulation inputs part. The expression is:

TimeAtHospitalThreshold + GAMM(TimeAtHospitalBeta,TimeAtHospitalAlpha).

The final block in this subsystem is the *Time Back To Station;* again a PROCESS block is used to simulate the travel time from the hospital, back to the station with the expression: *TravelTimesMatrix(AssignedHospital,AssignedStation).*

Subsystem 5: Disposal of a Call

Flow of the Subsystem 5 is described in Figure 5.9 below.

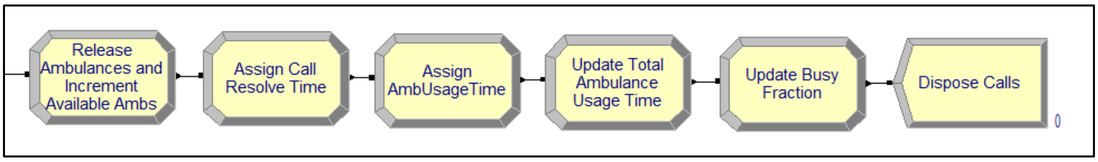

Figure 5.9. Simulation Flow of Subsystem 5

Subsystem 5 is a series of ASSIGN blocks for the final calculations of some parameters, and a DISPOSE block for the disposal of a call. This subsystem is run in either case: a hospital is needed or not, therefore, both Subsystems 3 and 4 are connected to the start of Subsystem 5. Subsystem 5 starts with an ASSIGN block, where the ambulance is released. This is done by incrementing AmbMatrix by one at the index of *AssignedStation*, and also *NoOfAvailableAmbulances* variable holding the number of available ambulances is incremented by one. The second block assigns an attribute named *ResolveTime* that is used to hold the duration of a *Call* in the simulation. Then another attribute *AmbUsageTime* is assigned. This is the total ambulance usage of a call, calculated by the expression *TNOW-DispatchTime-StartTime.* This value is added to the *TotalAmbUsage* variable at the next block. In the block labelled as *Update Busy Fraction,* the busy fraction is calculated with the expression: *TotalAmbUsage/(TNOW*TotalNoOfAmbs).* This means that the busy fraction is updated before each call is disposed at the final block labelled *Dispose Calls.*

5.4. Verification and Validation of the Simulation Model

In order to see whether the simulation model is accurately built and whether it is an accurate representation of the real emergency medical system, verification/validation of the simulation model is conducted by using some techniques. Since we do not have any real system parameters and statistics, we use a small data set and the data from the city of Adana for these purposes.

5.4.1. Subsystem Techniques

While building the simulation, to be able to test the subsystems individually, DECIDE blocks labeled *TestInterrupt ?* are placed in between subsystems as shown in Figure 5.10. The figure shows the transition between subsystems 1 and 2. If the *TestInterrupt* variable is set as “0”, then the entity flows through the second subsystem. However, if the variable is set a value “1”, entity does not continue and upon arriving at the DECIDE block, it is directed to and ends at the DISPOSE block.

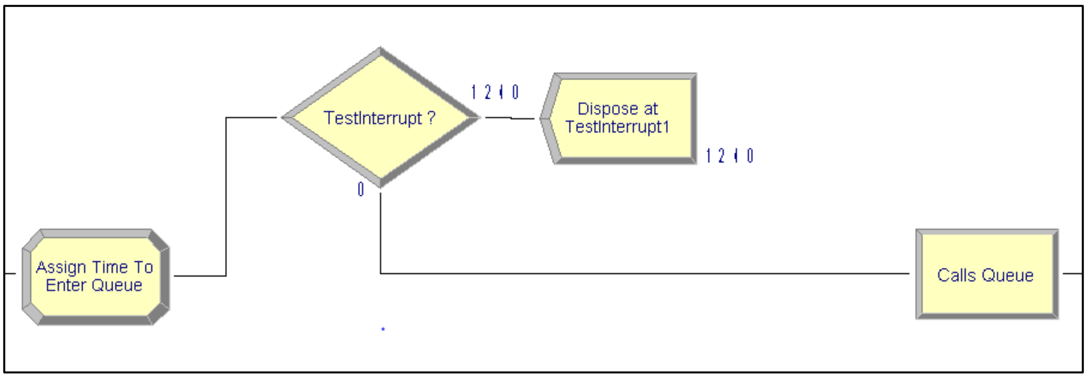

Figure 5.10. Visual Representation of Test Interrupt

The *TestInterrupt* is set to “1” to DISPOSE the entities between Subsystem 1 and Subsystem 2, and set to “2” to DISPOSE the entities between Subsystem 2 and Subsystem 3, and goes on like this. Therefore, the *TestInterrupt’s* value allows entities to flow up to that Subsystem and no more.

The subsystems are run one by one by means of this technique and tested one by one.

Data Set Used in Subsystem Technique

Simulation verification process is implemented by using a small data set to be able to track the entities easily, and to observe whether the blocks perform their tasks accurately. Therefore, we use 4 ambulances, 6 locations, and 2 hospitals in this data set.

Other data including average travel time between nodes, ambulance location matrix, hospital location matrix, and call probabilities of each location used in simulation verification are given in Appendix E.

For the verification tests, the simulation model is run for a single replication for 10,000 minutes.

Subsystem 1 Verification

Subsystem 1 is verified with the data set described in section 5.4.1 using the technique described in Section 5.4.2, setting *TestInterrupt* as “1” and the following related data are obtained and listed in Table 5.2.

Table 5.2. Results of Test Interrupt for Subsystem 1

Identifier	Average	Half Width	Minimum	Maximum	Observations
CC Process Delay	2.0044	0.03947	0.94665	4.2486	1240
CC Performing Time	2.0044	0.03947	0.94665	4.2486	1240
Identifier	Count	Limit			
Count NoOfAmbNotNeededCalls	0	Infinite			
Count Total No Of Calls	1240	Infinite			
Count NoOfAmbNeededCalls	1240	Infinite			

The Subsystem is verified to work correctly as *CC Performing Time* is very close to the mean set (which is “2”) and since *TotalNoOfCalls* equals *NoOfAmbNeededCalls,* meaning that all of the calls need ambulances, as we set the probability of this through the variable *pAmbNeeded* as “1”.

Subsystem 2 Verification

Subsystem 2 is verified with the data set described in section 5.4.1 using the technique described in Section 5.4.2, setting *TestInterrupt* as “2”. The difference between this and the previous one is that two additional blocks are added before the TestInterrupt’s DISPOSE block to delay the ambulances for a constant time of 20 minutes (so that we see some accumulation at the queue), and release the ambulance back to the system before disposal of the call. Significant statistics obtained from the run are given in Table 5.3.

Table 5.3. Results of Test Interrupt for Subsystem 2

Identifier	Average	Half Width	Minimum	Maximum	Observations
CC Performing Time	2.0053	0.02979	0.80904	3.9324	1295
Amb Setup Time Delay	2.0105	0.03024	0.94906	4.4631	1294
Time Spent At Queue	4.5	1.4898	0	41.946	1295
Dispatch Time	8.5191	1.4866	2.3246	46.922	1294

The data semantically verify our timing variables. Mean values are consistent with the values entered, and also we expect that average *Dispatch Time* is the summation of averages of *CC Performing Time*, *Amb Setup Time Delay* and *Time Spent At Queue*, and, in fact, omitting the small errors, this is the case. The small errors can be explained by the fact that some of the calls are waiting at the queue when the run is terminated. This means that they are taken into account while calculating *CC Performing Time*, but not taken into account in the calculation of *Time Spent At Queue* and not *Dispatch Time*, etc. Still, the error induced by this fact is very small (The difference between 8.5158 and 8.5191), and can be omitted to conclude that *Dispatch Time* is the sum of the other three time metrics, hence, calculations are verified.

The most important facility of the Subsystem 2, however, is the loop, the algorithm that selects the nearest possible ambulance to the *CallLocation*. The verification of this algorithm is done using Run Interaction feature of Arena.

In Figure 5.11, the blocks with rectangle around (Decrement Total Available Ambulances and Ambulance Setup Time Delay) indicate blocks where *breakpoints* are placed. The simulation run is stopped at these blocks, and some selected parameters can be viewed at those instances.

These two blocks are selected, as at the first one, the situation of available ambulances can be viewed, and the second one indicates the selected ambulance among available ones so that the result of the algorithm can be traced. An example trace is shown Figure 5.12.

Stop at the first block Stop at the second block

Figure 5.12. Watch List of Different Blocks

This example trace shows that at the first block (upper left corner) all 4 ambulances are available and call comes from *Location* index 3; the places of the ambulances are shown in the Watch 3 window on the lower left corner. Then the simulation continues and stops at the second block breakpoint. Now from the Watch 1 on the upper right corner, it is understood that the call is assigned to the second station. The *AmbMatrix(2,1)* is decremented by one as can be seen on the lower right corner. This verifies the virtue of the algorithm that the nearest possible ambulance is assigned to the call according to its station. The verification of the algorithm is done using this method described here for a series of different cases and replications.

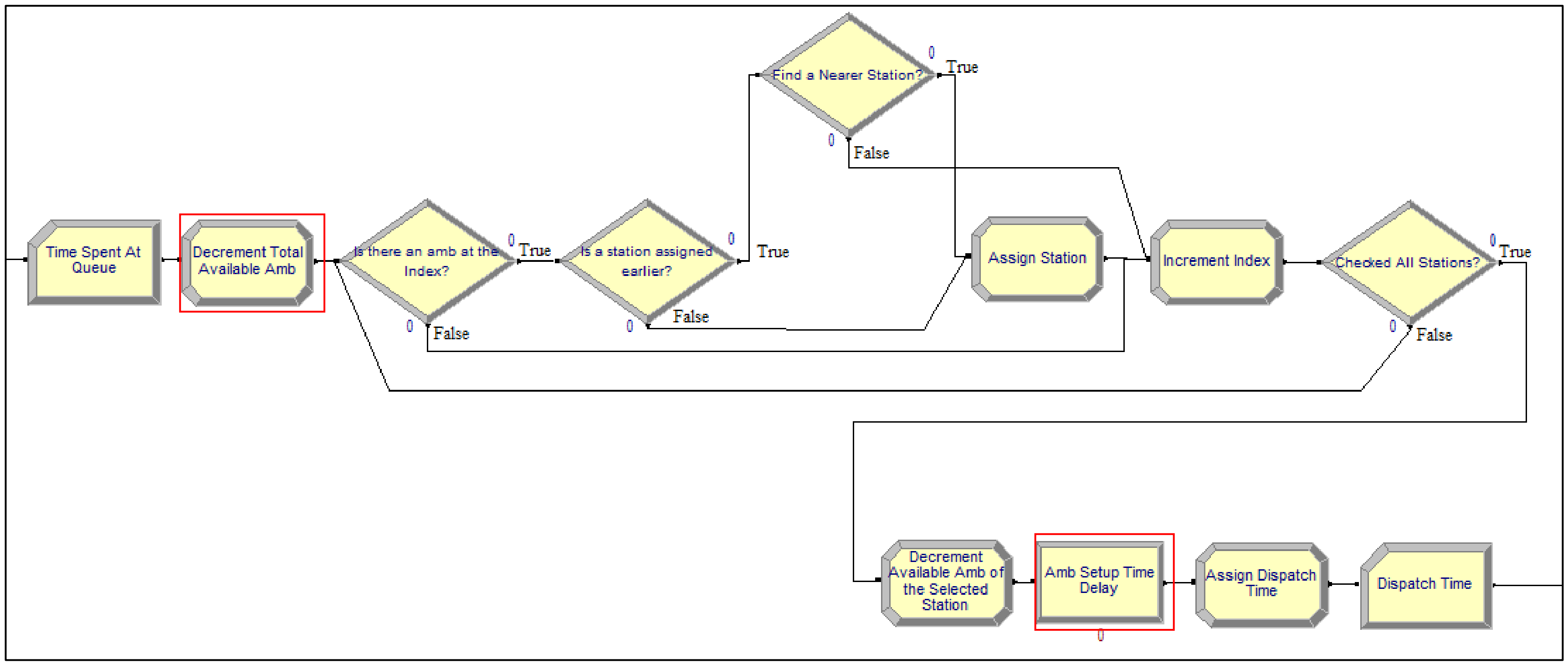

Figure 5.11. Visual Representation of Breakpoints

Subsystem 3 Verification

Subsystem 3 is verified with the data set described in section 5.4.1 using the technique described in Section 5.4.2. Since Subsystem 3 is related to mainly the ambulance travel times and 'at-scene' times, the focus will be on parameters related to these concepts. A test run yields the results in Table 5.4.

Table 5.4. Results of Test Interrupt for Subsystem 3

Identifier	Average	Half Width	Minimum	Maximum	Observations
TT Station to Scene Delay	5.0423	0.31555	0.66851	24.504	1215
Time At Scene Delay	10.056	0.41836	1.0382	50.982	1214
TT Scene To Station Delay	5.0291	0.44744	0.71918	20.793	778
Response Time	16.185	(Corr)	2.1155	74.121	1215

The results obtained are found to be consistent with the time distributions given. At the end of the run, an *entity* (call) is seen to be still in ambulance at scene state, since there is one observation difference between *TT Station to Scene Delay* and *Time At Scene Delay*. *Also TT Scene To Station Delay* is observed 778 times. This is also expected since some of the calls are of hospital needing type, their flow continues in Subsystem 4 before returning back to the station.

In this subsystem, some important variables such as response times, coverage and covered demand are calculated and assigned. The statistics are shown in Table 5.4 and 5.5. The calculation logic is verified using Arena Run Interaction toolbar with breakpoints and watches as described in the previous sections.

Table 5.5. Statistics of Test Interrupt for Subsystem 3

Identifier	Average	Half Width	Minimum	Maximum	Final Value
Coverage Value	0.44807	(Corr)	0	1	0.48026
Covered Demand Value	286.09	(Corr)	0	584	584

Subsystem 4 Verification

Subsystem 4 is also verified with the data set described in section 5.4.1 using the technique described in Section 5.4.2. Subsystem 4 deals with the interactions related to hospital and the focus is on the statistics related (Table 5.6).

Table 5.6. Results of Test Interrupt for Subsystem 4

Identifier	Average	Half Width	Minimum	Maximum	Observations
TT Scene To Hospital Delay	2.1931	0.10011	0.5217	4.9026	436
Time at Hospital Delay	6.7392	0.46132	1.0655	21.725	436
Time Back To Station	4.6724	0.45269	1.5	12	435

The time averages obtained are consistent with the time distributions of the variables. *Time Back To Station* is found to be slightly smaller than *TT Scene To Station* delay for example, this is because of the fact that, for the verification data set, the hospitals are located to be at two focal points of the location matrix (namely at 2nd and 5th indices). The observation numbers are also consistent.

The nearest ambulance selection algorithm is nearly identical to the nearest ambulance selection algorithm in Subsystem 2, and therefore verified using the same techniques described in Subsystem 2 verification, using breakpoints and watch lists of the Arena Run Control.

Subsystem 5 Verification

Subsystem 5 is also verified with the data set described in section 5.4.1 using the technique described in Section 5.4.2. Subsystem 5 is a small subsystem only dealing with the assignments of final variables and then the disposal of the call.

Attribute *AmbUsageTime*, variable *TotalAmbUsageTime* and most importantly *BusyFraction* variable is assigned in this subsystem. The variable calculation logic is verified by using Arena's Run Control, stopping at breakpoints and checking for each call entity as described in the previous sections.

5.4.2. Other Techniques

Data Set

Other techniques are implemented by using the data for the City of Adana. Some information is given about this data in the previous chapters, so we present here only the distributions and constants input to the simulation model.

Initial values of the variables used in the simulation model for this data are given in Appendix F. Other data including ambulance location matrix, and hospital location matrix used in one of the models in this section are given in Appendix G. Average travel time matrix is already given in Table B.2 in Appendix B. This matrix is also used in the simulation models as is.

Input Distributions Control

Various analyses related to input distributions and their parameters used in the simulation model are conducted in Minitab to control whether they represent the randomness in the system correctly. Thus, we can detect how appropriate the usage of the input distributions and parameters are.

Call arrival distribution is determined as exponential distribution as stated in 5.2.4, and the arrival rate is determined as 3.523 according to the demand data of Adana case. We generate random data distributed exponentially in Minitab and plot histogram of this data. This can be seen in Figure 5.13.

Control center processing time distribution and ambulance setup time are determined as Lognormal, and we use LOGN (2, 0.5) as an input to the simulation model. We generate this data and plot its histogram in Minitab to see the behavior of these values in simulation (Figure 5.14).

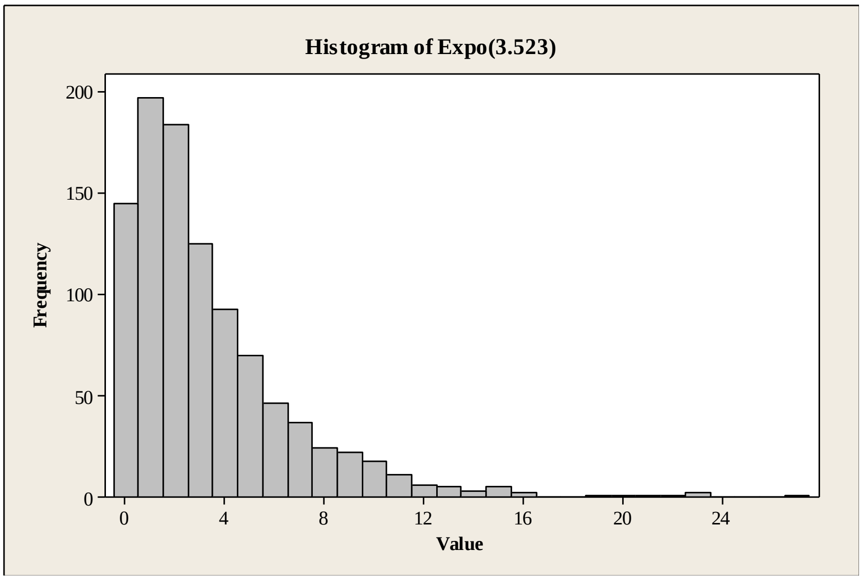

Figure 5.13. Histogram of Expo (3.523)

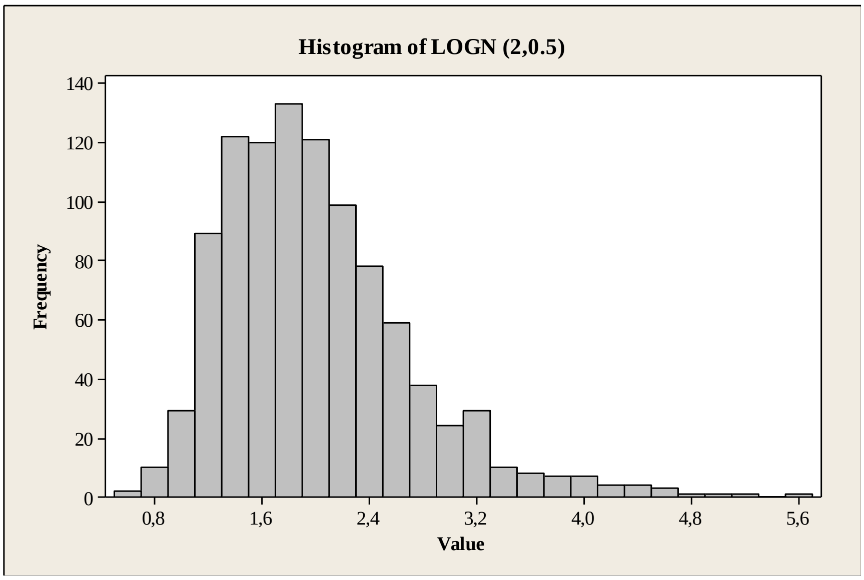

Figure 5.14. Histogram of LOGN (2, 0.5)

These values are consistent with the nature of these tasks. Control center processing time may be short in the well-defined cases (during triage), but may be long in the complicated cases. Ambulance setup time may also be short in the cases that do not need new equipment or material, but very long in the cases that need some extra equipment or material to load into the ambulance. So this time range makes sense for both control center processing time and ambulance setup time.

We use Gamma distribution for time at the scene and time at the hospital. 1+GAMM(1.2,7.5) for time at the scene and 1+GAMM(1,4) for time at the hospital are used in the simulation. The reason of using these values is to obtain mean values as 10 (1+1.2*7.5) and 5 (1+1*4) that are used in the busy fraction estimation in the mathematical model, G-MEXCLP; so, they are compatible to the values used there in. We create random data which have Gamma distribution with these parameters and plot their histograms (in Figures 5.15 and 5.16).

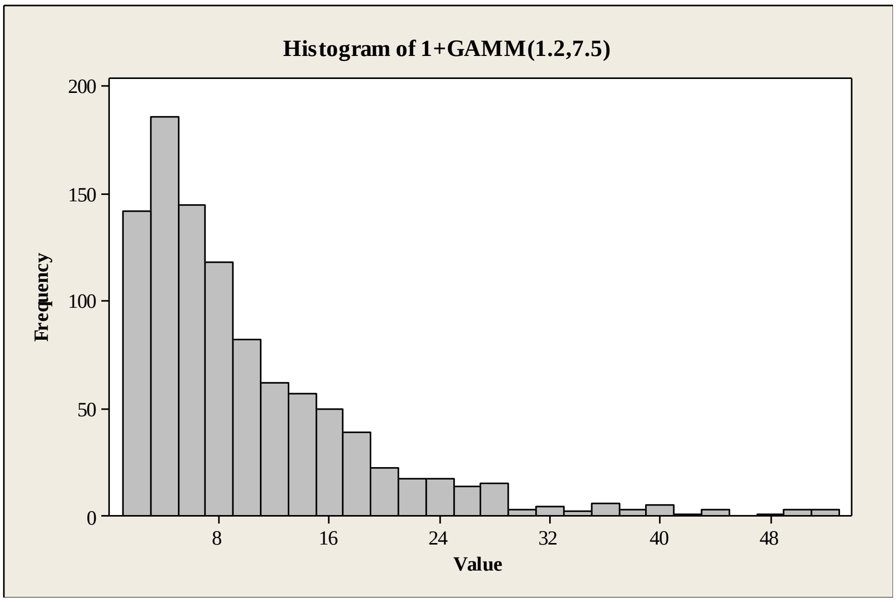

Figure 5.15. Histogram of 1+GAMM (1.2, 7.5)

The reason of using these mean values is that these tasks usually result in these mean times; however, these values may sometimes be shorter or occasionally very high. These histograms seem to be very consistent with this purpose.

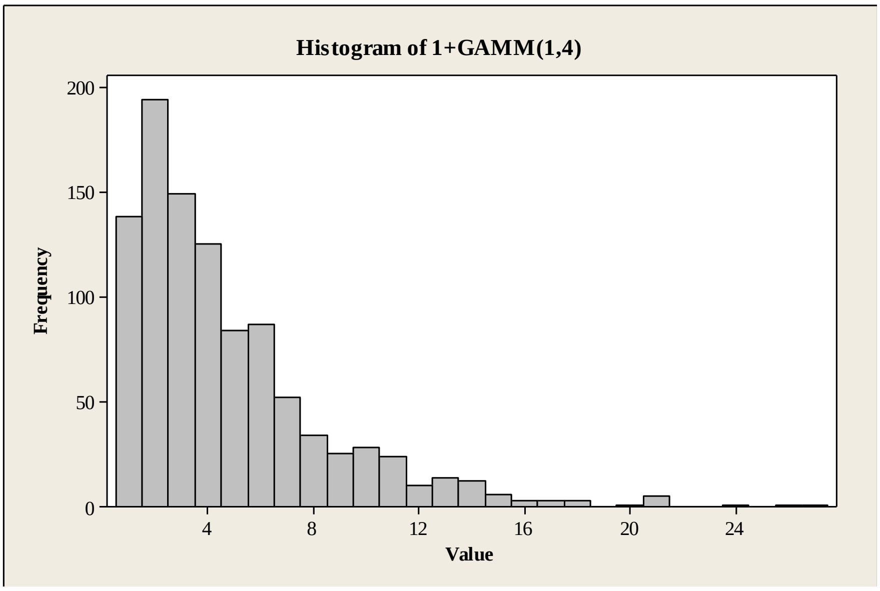

Figure 5.16. Histogram of 1+GAMM (1, 4)

Moreover, lognormal distribution is used for all travel times. Mean of this distribution is taken from the "average travel time between nodes" matrix, and variance is used as 0.25 times of the mean. Therefore, we create and plot histogram of some potential travel times. These can be seen in Figures 5.17 and 5.18.

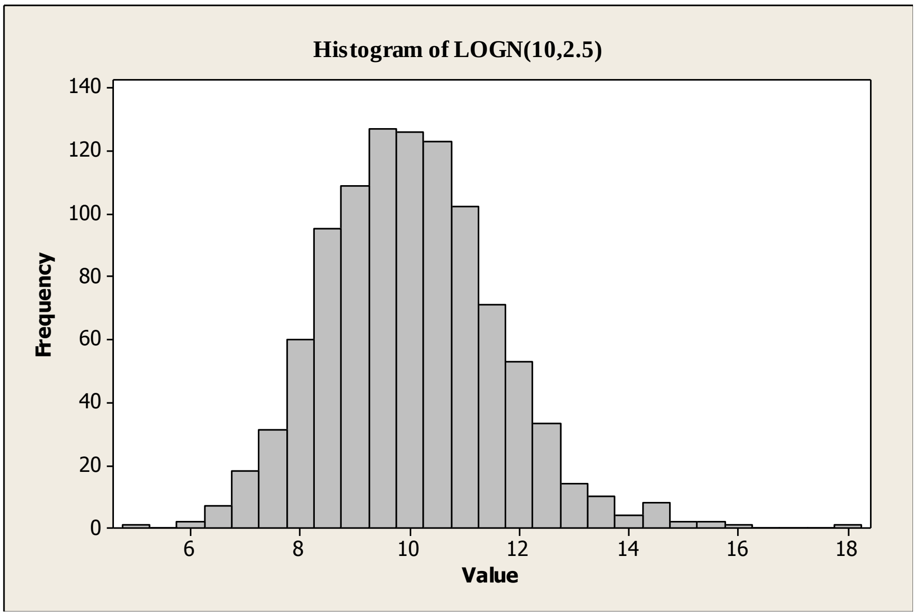

Figure 5.17. Histogram of LOGN (10, 2.5)

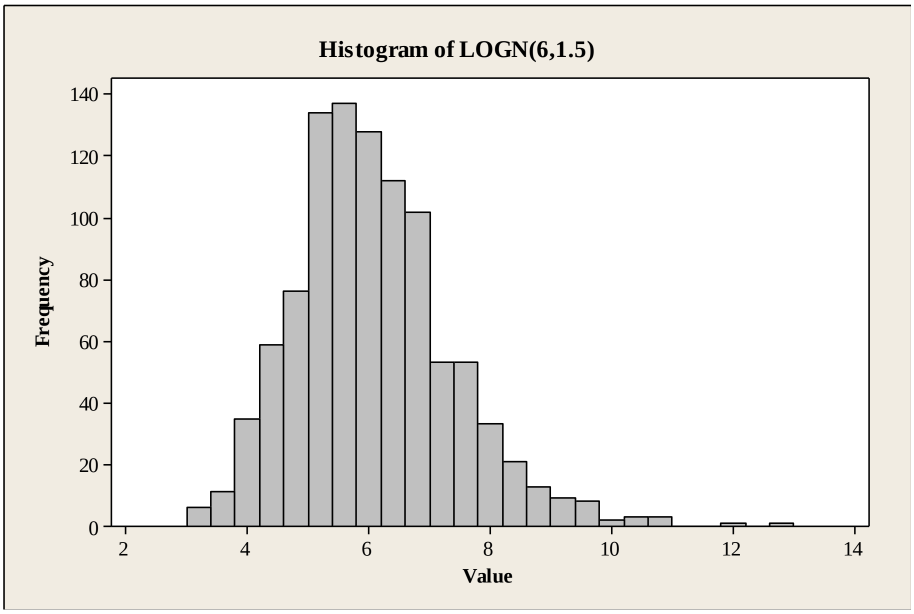

Figure 5.18. Histogram of LOGN (6, 1.5)

Increasing Arrival Rate

We compare multiple systems in the simulation model to see how simulation results change with changing arrival rates of emergency calls. In actual EMS systems, arrival rate is a very important input of the system, and the system reacts quickly to the variation in the interarrival time between calls. For example, if interarrival time between calls is increased, and thus frequency is decreased, response time should decrease and busy fraction should increase.

Before making simulation runs, steady state behavior of the system is investigated. One year simulation run for the most congested system whose interarrival rate is 3.523 is conducted. Moving average graphs are plotted for all of the three performance measures, and they are presented in Figure 5.19, 5.20 and 5.21.

According to these graphs, truncation points and replication length are determined as 80,000 minutes and 100,000 respectively. So simulation is run with 10 replications for the time interval [80,000; 100,000].

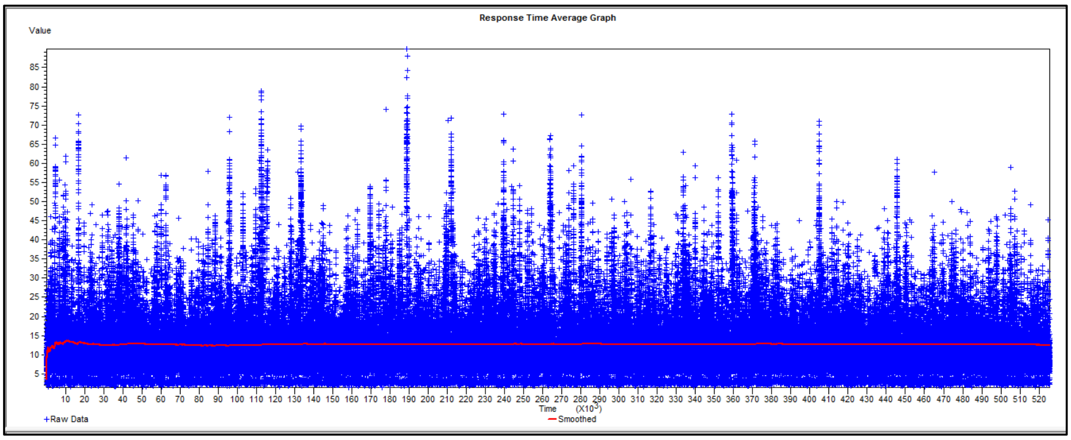

Figure 5.19. Mean Response Time by Simulation Length

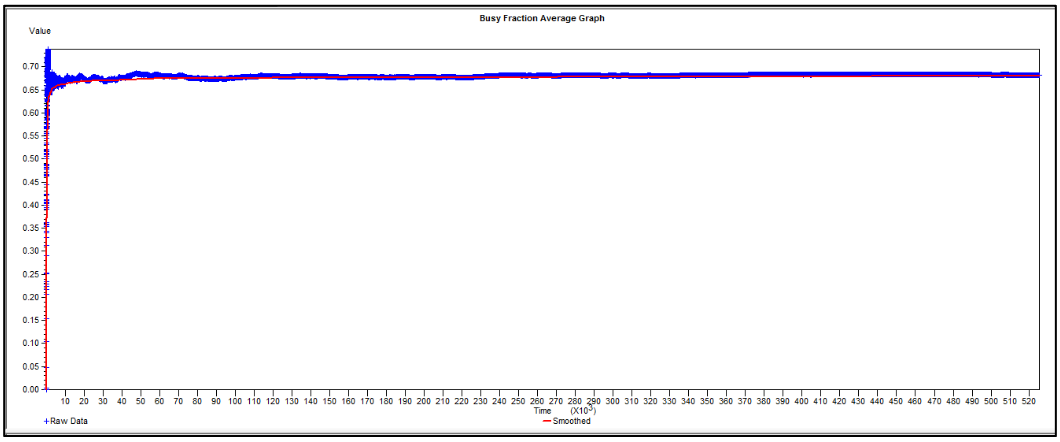

Figure 5.20. Mean Busy Fraction by Simulation Length

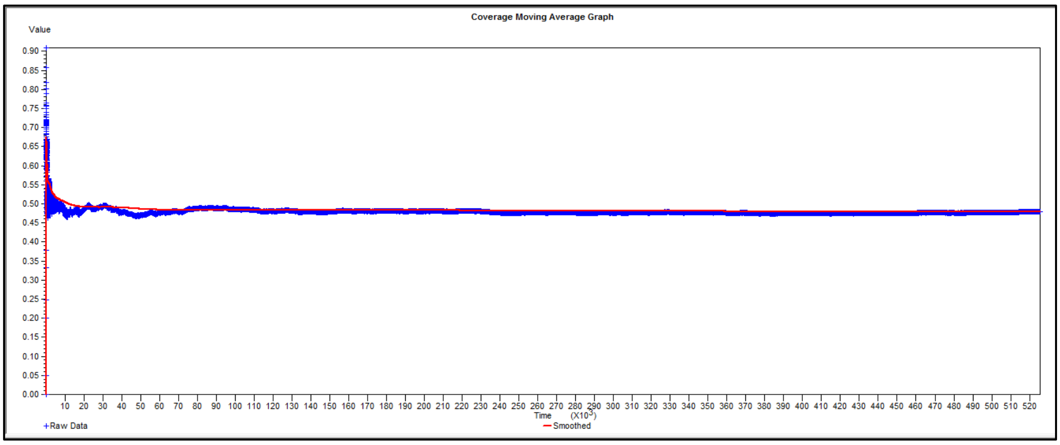

Figure 5.21. Mean Coverage by Simulation Length

Three different interarrival rates of exponential distribution are used as λ=3.523, λ=7 and λ=10. Then replication averages of the three performance measure are compared with respect to these interarrival times. According to the following box plot of replication averages for response time, busy fraction and coverage (Figure 5.22, 5.23, 5.24), it seems that simulation model accurately reflects the real EMS system.

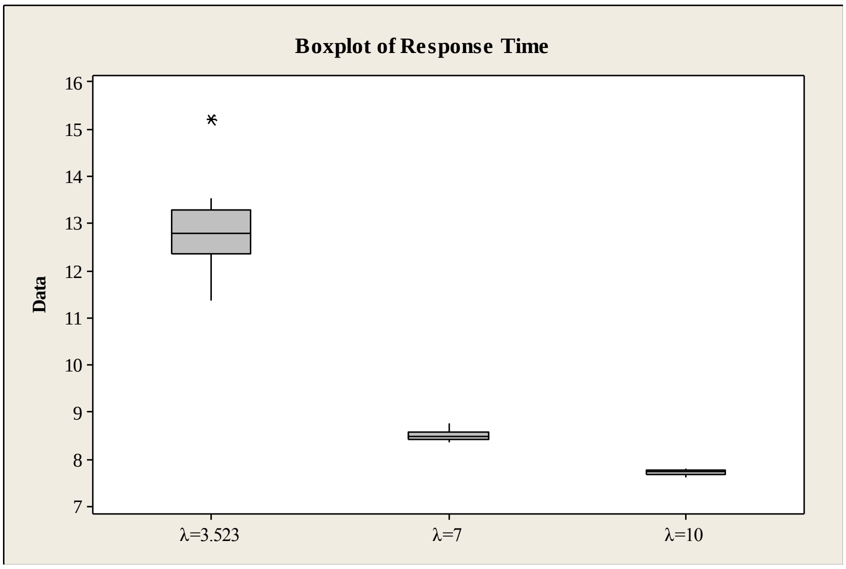

Figure 5.22. Boxplot of Response Time for Different Interarrival Times

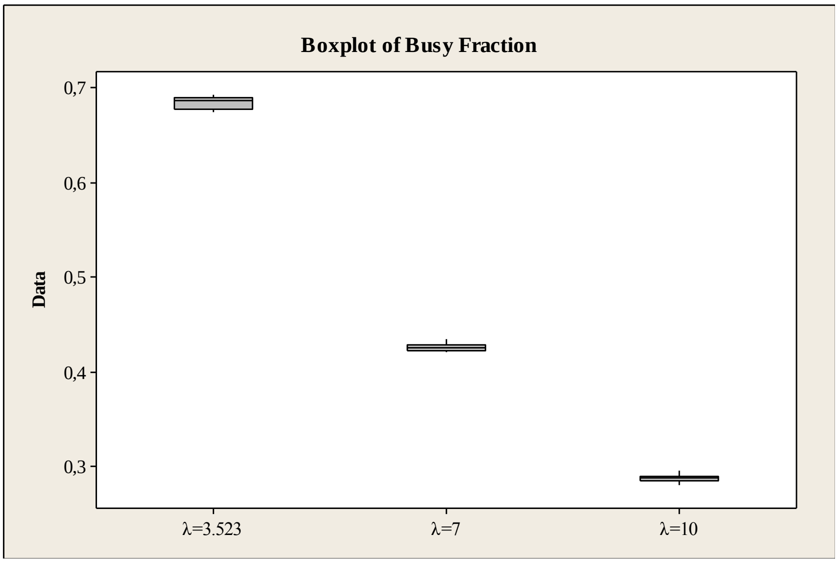

Figure 5.23. Boxplot of Busy Fraction for Different Interarrival Times

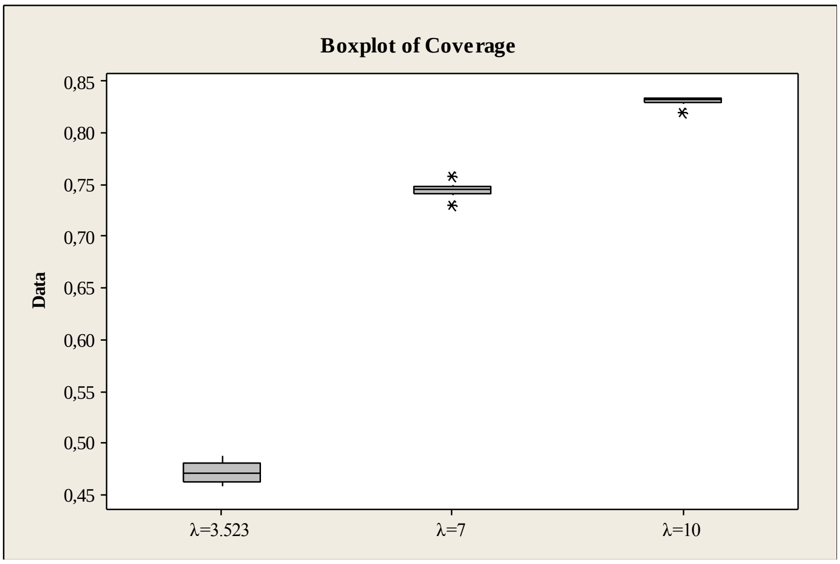

Figure 5.24. Boxplot of Coverage for Different Interarrival Times

As expected, when interarrival times between calls are increased, response time and busy fraction decrease significantly while coverage increases.

All Resources at One Location

All ambulances are located at one location, as an example, at node 63, to see the behavior of the simulation model in such an extreme case. We run the simulation for 300,000 minutes and investigate the steady state behavior. Moving average graph for response time is plotted in Figure 5.25.

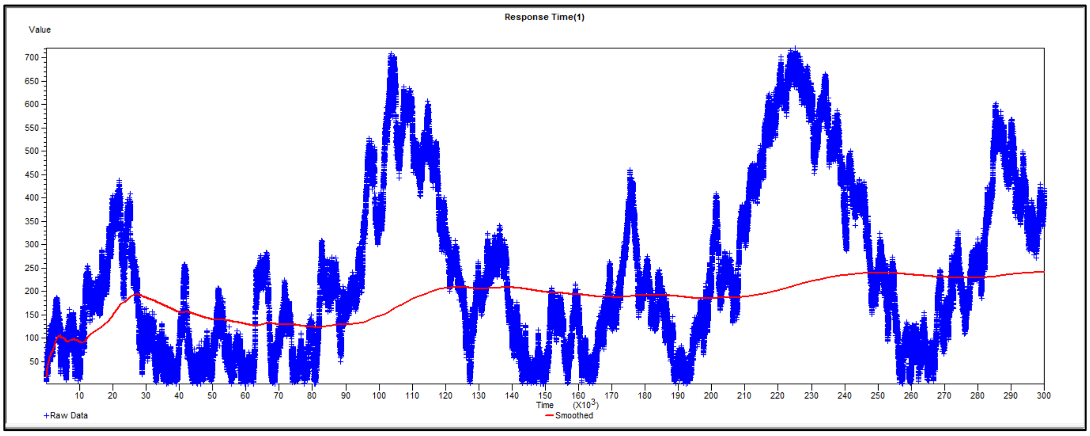

Figure 5.25. Response Time by Simulation Length

As it can be seen in Figure 5.25, response time values are very high when all ambulances are located at one location, and the system does not reach the steady state.

Force Starvation

We can see the starving behavior of the simulation model with the decreasing arrival rate and increasing number of ambulances. For this purpose, the number of ambulances is doubled at each location, and arrival rate is set as $\lambda=10$. Simulation model is run for 10 replications for the interval [80,000; 100,000]. Replication averages of the performance measures are obtained as in Table 5.7.

Table 5.7. Average Values of Performance Measures in Starvation Case

	Mean	StDev	95%CI
Response Time	6.8447	0.0442	[6.8130, 6.8764]
Busy Fraction	0.063502	0.000715	[0.062990, 0.064014]
Coverage	0. 927570	0. 002215	[0.925985, 0.929155]

According to these results, average busy fraction of the ambulances is very small. All ambulances wait at their station for most of the time. Therefore, when there are many ambulances, and call arrival rate is low, the system faces starving condition.

Degenerate Test

The degeneracy of the model's behaviour can be tested by taking the interarrival time between calls as $\lambda=1$ while not increasing the number of ambulances which is already taken as 13. Thus, the arrival rate of the system can be made larger than the service rate. Simulation model is run for 40,000 minutes by using this input parameter, and the following results are obtained for each performance measure as shown in Table 5.8.

Table 5.8. Outputs of the Case for λ=1, P=13

Performance Measure	**Average Value**
Response Time	13211 Min
Time in Queue	13,202
Busy Fraction	94.19%
Coverage	0.16%
Number In Queue	13215

As it can be seen in Table 5.8, if arrival rate is larger than the service rate, average number in the queue continues to increase over time, and response rate and busy fraction are extremely high than the acceptable values, as expected. So this technique provides satisfactory results.

CHAPTER 6

THE PROPOSED SOLUTION APPROACH

Mathematical models in the literature suggested for Emergency Medical Service Systems, despite being as detailed and finical as possible, generally fall short in fully reflecting the real world. Many simplifying assumptions are made to handle several sources of uncertainty. Moreover, performance measures of the system such as demand coverage, response time are not measured properly due to the inadequacies of the mathematical models developed so far. For example, many mathematical models overestimate the coverage because of their inadequacy in estimating the time when ambulances are busy (Repede and Bernardo, 1994). On the other hand, approaches to the problem with the incorporation of simulation models as well, better reflect real world assets, but may not yield the optimal locations for ambulances as the mathematical models can. These simulation models built for EMS systems are generally used for evaluating the existing EMS systems, or for testing the impact of change when moving to a new system. Therefore, the ambulance location and allocations are known prior to simulation, making the simulation a tool for assessing performance rather than a tool to decide on the location and allocation of stations and ambulances.

We propose an integrated optimization and simulation approach to take advantages of both the mathematical modelling's ability to find the optimal locations for the ambulances, and the simulation modelling's power to evaluate the performance of EMS systems in a more realistic manner. Our approach allows us to evaluate the operational performance of the ambulance location plan obtained from the mathematical model through a detailed simulation model. Mathematical model is used to find the initial locations of the ambulances using some initial parameter settings. Then ambulance locations are input to the simulation model in order to evaluate the performance of the system in a stochastic environment in which the arrival time of calls, travel times, service times are all uncertain as they are in the real world. If the performance of the system is not found to be satisfactory, the mathematical model is reconstructed by the updated parameters.

Our integrated approach involves the G-MEXCLP model as the mathematical model and the simulation model which is actually a generic EMS model. These two models are used in an iterative manner so as to improve the solution to the ambulance location and allocation problem of the EMS system. Figure 6.1 shows the logical flow of the integrated approach.

According to our approach, iterations start with the construction of the G-MEXCLP model with its initial parameters. Throughout the iterations, some of the parameters of the G-MEXCLP are updated, while some others are not changed. Average travel time between nodes and average demand of each node are the only constant input parameters of the model, while the number of available ambulances and busy fraction of each ambulance are parameters that can be updated throughout the iterations. Iterations begin with the construction of the G-MEXCLP model with the initial parameters; then it is solved to obtain ambulance locations, and number of ambulances at each location. If the problem is infeasible, G-MEXCLP model is reconstructed with one more ambulance added in the fleet, and busy fraction is estimated for the updated number of ambulances.

Thus, second iteration begins with these updated parameters. When the G-MEXCLP model gives a feasible solution for the ambulance locations plan, ambulance locations and number of ambulances are used as input parameters to be updated together with the other constant (i.e., not changing during iterations) input parameters such as the average travel time between locations, interarrival time between calls, control center performing time, ambulance setup time, and times at the incident scene and hospital. Then simulation model is run with these parameters

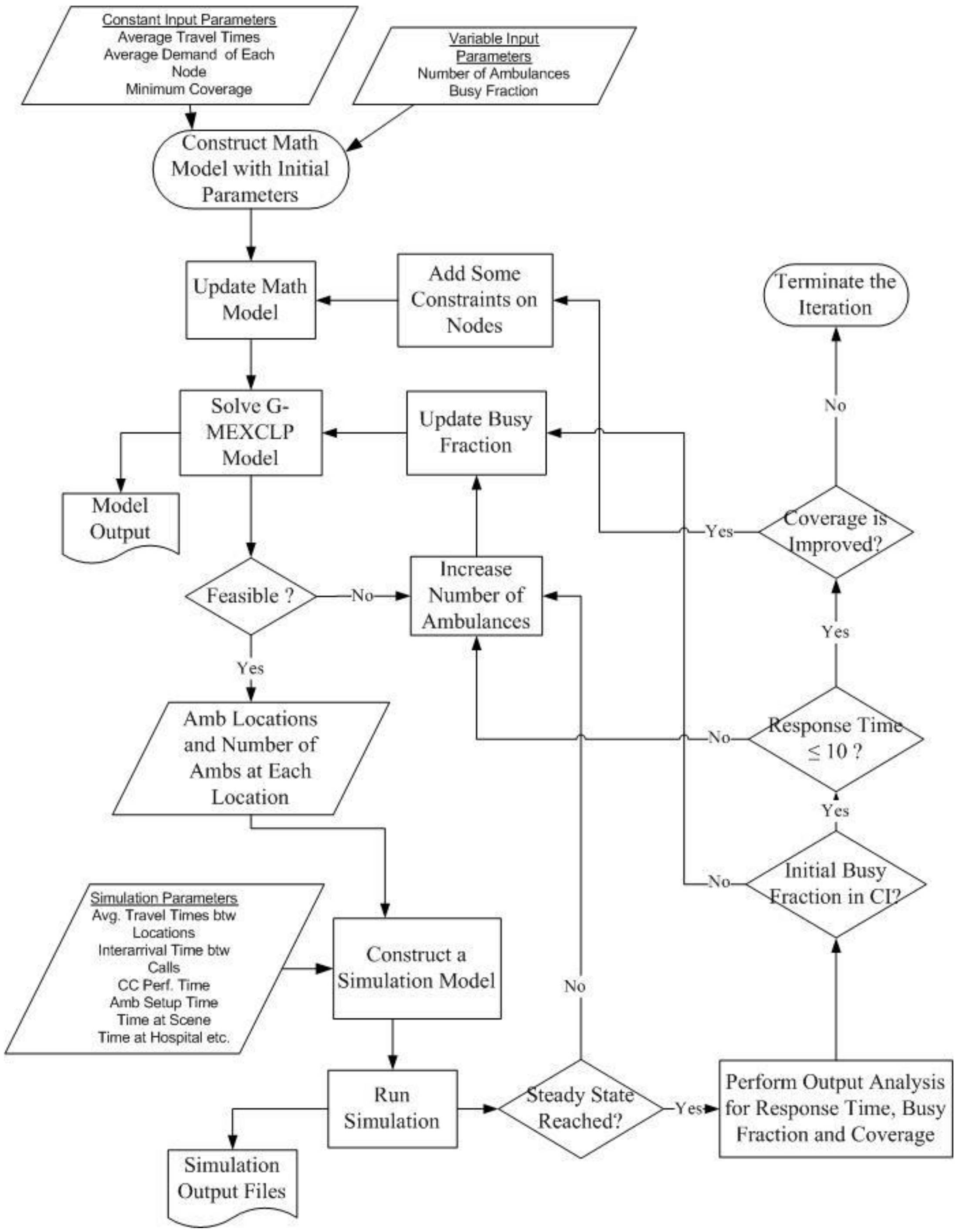

Figure 6.1. Integrated Optimization and Simulation Approach for the EMS System

to observe the performance of the system in terms of busy fraction, response time and demand coverage as the key performance measures. So these performance measures are analyzed to decide whether the system reaches the steady state. If not, a new iteration is started again with the increased number of ambulances.

If the system reaches the steady state, output analysis is performed on these values obtained from many replications of the simulation model. The number of replications is also decided to achieve the required precision for these performance measures. 95% confidence interval is constructed for the three performance measures. Busy fraction is the first performance measure to be examined in this integrated approach. If both the estimated and the initial busy fractions at the start of the G-MEXCLP model construction do not fall in this interval, this initial busy fraction value is exchanged with the mean of the CI constructed for the busy fraction. So, the third iteration begins with the busy fraction updated only keeping the same number of ambulances.

The purpose of these updates is to reach the correct value of busy fraction for the determined number of ambulances. As a result, a correct combination of busy fraction and number of ambulances values are obtained. These new parameters are again input to the G-MEXCLP model and new ambulance locations are obtained; thus, the third iteration begins.

If, in the second iteration, the estimated and the initial busy fraction values at the start of the G-MEXCLP model fall in the CI interval for the busy fraction, the iterations continue with the response time check.

In the third iteration, if the ambulance locations do not differ from those in the second iteration, iterations again continue with the response time check.

In this part of the approach, if the upper limit of CI constructed for the response time turns out to be greater than 10 minutes, which is the target response time value for this problem set, the next iteration begins with the increased number of ambulances, and continues in a way similar to the previous iterations. If the CI includes 10 minutes, or it is less than 10 minutes, iterations go onwith the check of the demand coverage.

Up to this point of the algorithm, busy fraction is adjusted and response time is brought up to the desired level according to the step of the flow in the approach. After this point, coverage is improved as much as possible. This improvement is achieved with some constraint addition/deletion to/from the G-MEXCLP model. According to the simulation model results, some constraints that force higher coverage for nodes which have higher response times can be added while omitting the mandatory coverage constraint, (4). The reason for removing the mandatory coverage constraint is not to over-restrict the system by adding too many constraints and cause it to underperform. It is important to state here that, for some of the test runs, that was indeed the case. Hence, demand points that have higher response times are favored instead of covering all demand points at least at one of the coverage levels.

This constraint addition process can continue until no more improvement is obtained in coverage or coverage gets worse than it was in the previous iterations.

CHAPTER 7

COMPUTATIONAL STUDY

Solution approach proposed in the previous chapter is tested with the data for the City of Adana. The detailed description of the data characteristics are given in the mathematical model validation part. Some initial computational studies on the mathematical model, G-MEXCLP, and the simulation model are conducted in their verification and validation processes. Therefore, in this chapter, we perform a computational study on our integrated approach.

Each iteration of the approach can be defined as the process that begins with the construction of the G-MEXCLP model with its initial original parameters, and ends with the re-construction of the G-MEXCLP model with the updated parameters and/or deletion/addition of some constraints, or ends at the termination part.

7.1.Testing Our Solution Approach

1st Iteration

This iteration begins with scenario 2.2 in Table 4.4 in section 4.2.2.3, which is the first scenario that gives a feasible solution to the G-MEXCLP model. The variable input parameter settings and the solution of the model are presented in Table 7.1.

Table 7.1. Model Inputs and Solutions for the 1th Iteration

Number of Ambulances	Busy Fraction	Ambulance Location Nodes
11	0.78	11,15,16,25(2),31,39,41,53,57,62

Simulation model is constructed and run for one year. However, it can be seen from Figure 7.1 that response time value goes down after 120,000 min, but it does not reach the steady state even in one year. Therefore, this iteration ends with the increased number of ambulances.

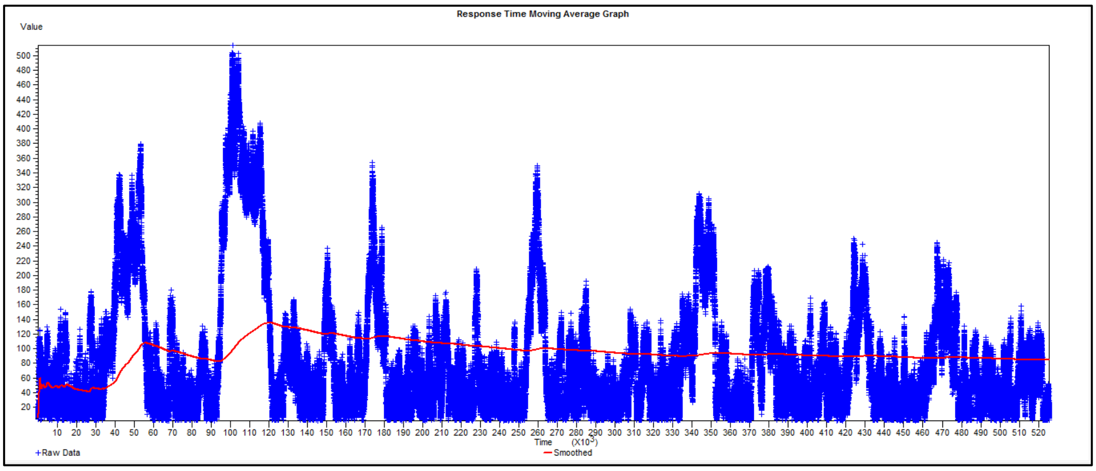

Figure 7.1. Mean Response Time by Simulation Length for the 1st Iteration

<u>2nd Iteration</u>

Based on the decision obtained from the previous iteration, number of ambulances is increased by one, and 2nd iteration continues with scenario 2.3 in Table 4.4 in section 4.2.2.3 whose parameter settings and solution are as in Table 7.2

Table 7.2. Model Inputs and Solutions for the 2th Iteration

Number of Ambulances	Busy Fraction	Ambulance Location Nodes
12	0.71	5,11,15,17,23,27,31,35,51,53,57,62

Simulation model is constructed and run for one year, and the outputs for the performance measures (response time, busy fraction and coverage) are analyzed to see the steady state behavior, and determine the truncation point. Moving average graphs are plotted for the three performance measures. These can be seen in Figures 7.2, 7.3 and 7.4.

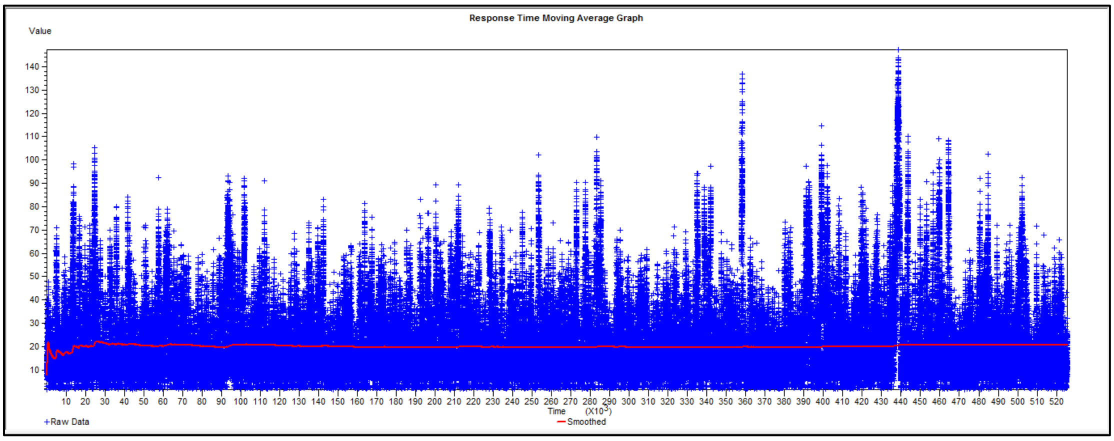

Figure 7.2. Mean Response Time by Simulation Length for the 2nd Iteration

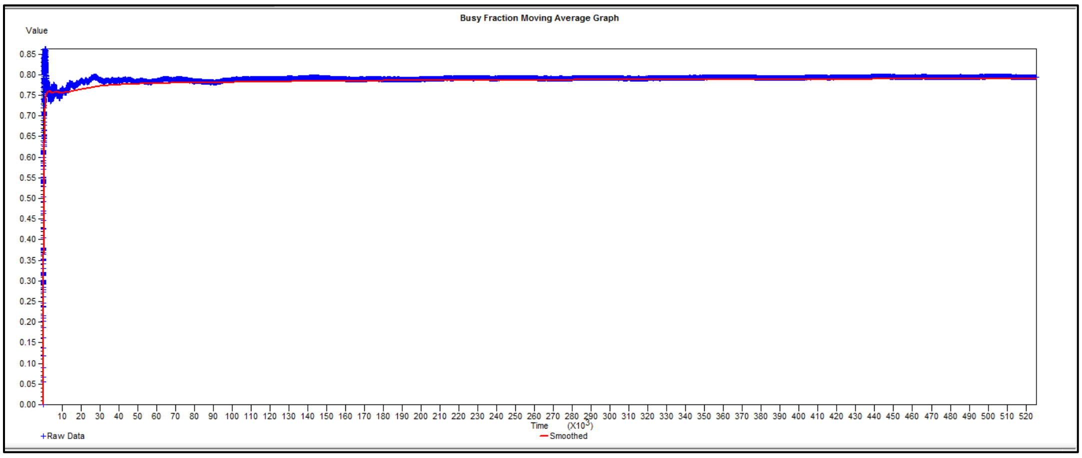

Figure 7.3. Mean Busy Fraction by Simulation Length for the 2nd Iteration

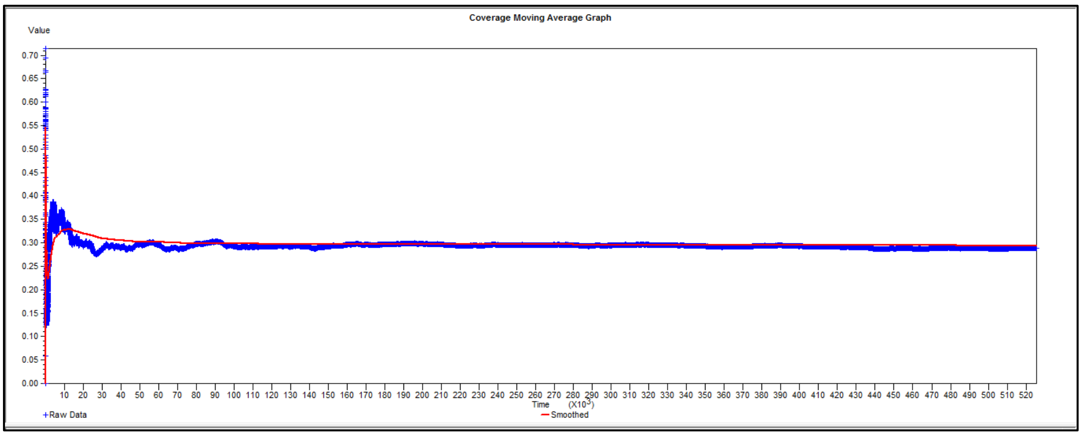

Figure 7.4. Mean Coverage by Simulation Length for the 2nd Iteration

According to these graphs, it is seen that the system reaches the steady state at 100,000 minutes. However, truncation point is determined as 120,000 minutes to be conservative, and statistics accumulated up to 120,000 minutes are not used. Since the replication length is determined as 300,000 minutes, statistics for 180,000 minutes are collected to interpret the results.

Initially, we start with 10 replications (*N*=10) for the time interval [120,000; 300,000], and construct a 95% confidence interval for the three performance measures using the replication averages. Confidence intervals are obtained as in Table 7.3.

Table 7.3. 95% Confidence Intervals on Performance Measures

Performance Measure	N	Mean	StDev	SE Mean	95% CI
Busy Fraction	10	0.79430	0.00494	0.00156	[0.79077, 0.79784]
Response Time (min)	10	20.426	0.706	0.223	[19.921, 20.931]
Coverage	10	0.28963	0.00948	0.00300	[0.28285, 0.29642]

Results of these initial 10 replications from the output files are as follows:

Precision for busy fraction = $\frac{\text{Half Width}}{\text{Mean}} = \frac{0.00354}{0.79430}$ = 0.00445 = 0.445%

Precision for response time = $\frac{\text{Half Width}}{\text{Mean}} = \frac{0.505}{20.426}$ = 0.024723 = 2.47%

Precision for coverage = $\frac{\text{Half Width}}{\text{Mean}} = \frac{0.006785}{0.28963}$ = 0.023426 = 2.34%

These precision values are considered as strong enough; hence, we do not need any more replication to interpret the outputs.

According to the solution approach flowchart that was described in the previous chapter, the first performance measure that should be analyzed in conducting the iterations is the busy fraction. Since the initial busy fraction value is 0.71, and it is not in the confidence interval, the next iteration begins by updating the busy fraction value as 0.7943 (the mean value of simulation output) to be used in the G-MEXCLP model.

3rd Iteration

Based on the decision obtained from the previous iteration, busy fraction is updated as 0.7943 and this 3rd iteration continues with the following parameters given in Table 7.4.

Table 7.4. Model Inputs for the 3rd Iteration

Number of Ambulances	Busy Fraction
12	0.7943

G-MEXCLP model is reconstructed with these parameters, and the ambulance location nodes are obtained as in Table 7.5.

Table 7.5. Model Inputs and Solutions for the 3th Iteration

Number of Ambulances	Busy Fraction	Ambulance Location Nodes
12	0.7943	5,11,15,17,23,27,31,35,51,53,57,62

So the new ambulance locations are not different from the previous ambulance location nodes, so the iteration continues with the response time check obtained in the previous iteration. Confidence interval for the response time is obtained as [19.921, 20.931]. Since this interval is much larger than the target response time (10 minutes), iterations are carried out with the updated number of ambulances; and the next iteration begins.

4th Iteration

Based on the decision obtained from the previous iteration, number of ambulances is increased by one, and this 4th iteration continues with scenario 2.4 in Table 4.4 in section 4.2.2.3 whose parameter settings and the solution of the model are in Table 7.6.

Table 7.6. Model Inputs and Solutions for the 4th Iteration

Number of Ambulances	Busy Fraction	Ambulance Location Nodes
13	0.66	5,8,11,15,17,23,27,31,35,51,53,57,62

Simulation model is constructed and run for one year, and the outputs for the performance measures (response time, busy fraction and coverage) are analyzed to see the steady state behavior and determine the truncation point. Moving average graphs are plotted for the three performance measures. These can be seen in Figures 7.5, 7.6 and 7.7.

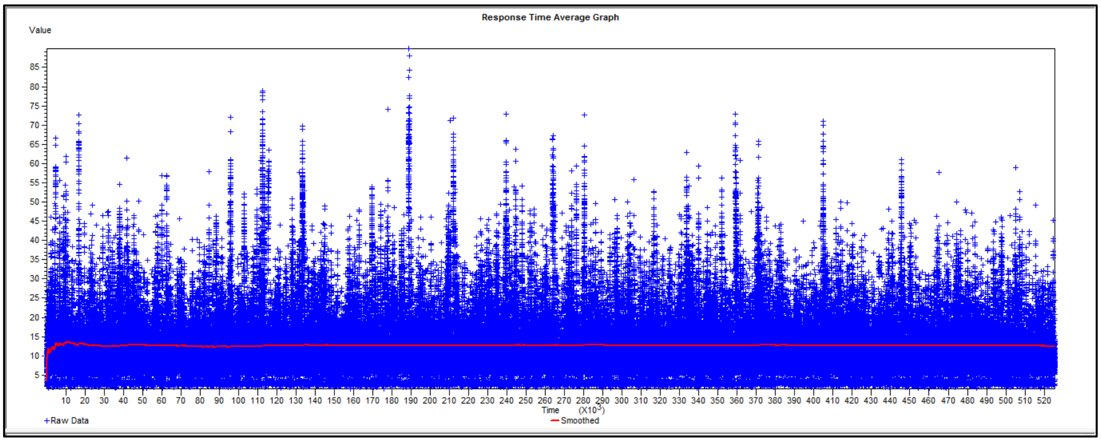

Figure 7.5. Mean Response Time by Simulation Length for the 4th Iteration

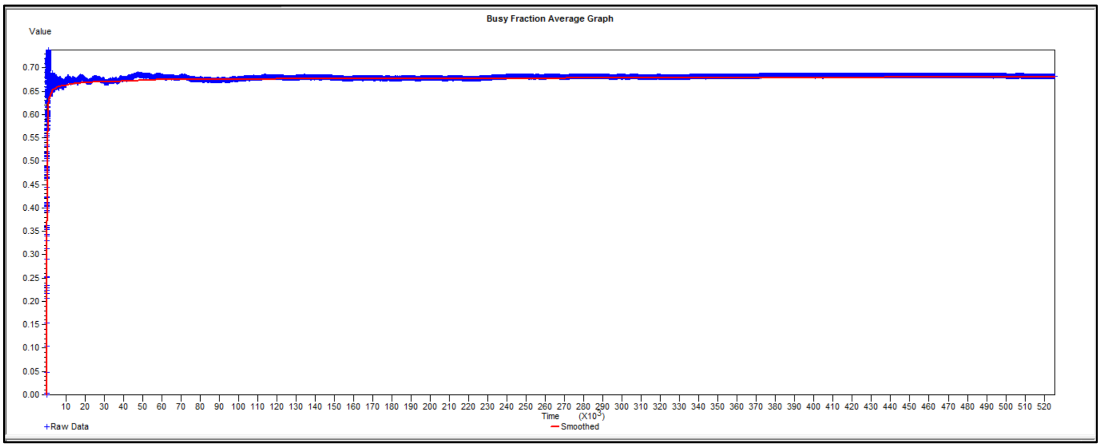

Figure 7.6. Mean Busy Fraction by Simulation Length for the 4th Iteration

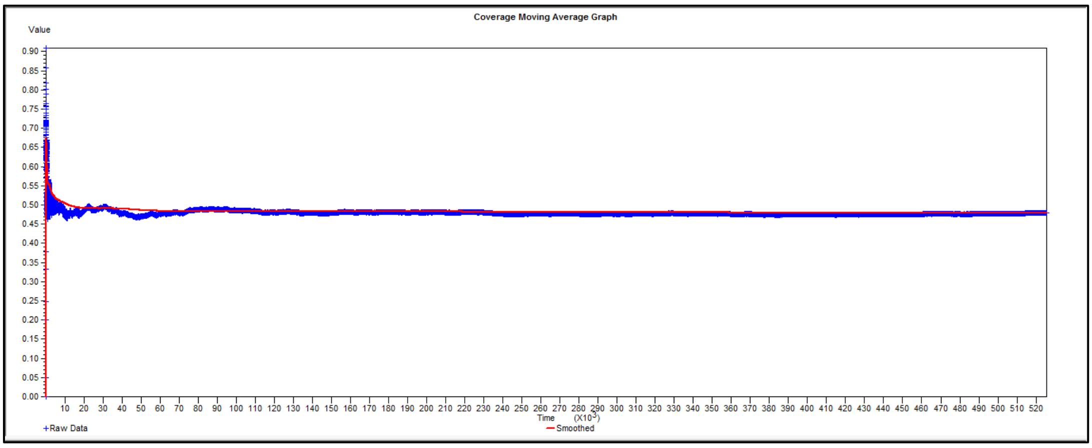

Figure 7.7. Mean Coverage by Simulation Length for the 4th Iteration

According to these graphs, it is seen that the system again reaches the steady state at 100,000 minutes. Therefore, truncation point and replication length are determined as in the second iteration. We run the simulation model with 10 replications for the time interval [120,000; 300,000], and construct 95% confidence interval for the three performance measures using the replication averages. Confidence intervals are obtained as in Table 7.7.

Table 7.7. 95% Confidence Intervals on Performance Measures

Performance Measure	N	Mean	StDev	SE Mean	95% CI
Busy Fraction	10	0.68562	0.00335	0.00106	[0.68323,0.68802]
Response Time	10	12.8862	0.198	0.0626	[12.7446,13.0278]
Coverage	10	0.47034	0.00542	0.00171	[0.46646,0.47422]

Results of these initial 10 replications from the output files are as follows:

Precision for busy fraction = $\frac{\text{Half Width}}{\text{Mean}} = \frac{0.004789}{0.68562} = 0.006986 = 0.70\%$

Precision for response time = $\frac{\text{Half Width}}{\text{Mean}} = \frac{0.2832}{12.8862} = 0.021977 = 2.20\%$

Precision for coverage = $\frac{\text{Half Width}}{\text{Mean}} = \frac{0.00776}{0.47034} = 0.016499 = 1.65\%$

These precision values are considered as strong enough; hence, we do not need any more replication to interpret the outputs.

According to the solution approach flowchart, the first performance measure that should be analyzed is the busy fraction. Since the initial busy fraction value is 0.66, and it is not in this confidence interval, the next iteration begins by updating the busy fraction value as 0.6856 (mean value in the simulation model) to be used in the G-MEXCLP model.

5th Iteration

Based on the decision obtained from the previous iteration, busy fraction is updated 0.6856 and this 5th iteration continues with following parameters as in Table 7.8.

Table 7.8. Model Inputs for the 5th Iteration

Number of Ambulances	Busy Fraction	MIP Objective	Solution Time (sec)
13	0.6856	9171.84	13.28

G-MEXCLP model is reconstructed with these parameters and the ambulance location nodes are obtained as Table 7.9.

Table 7.9. Model Inputs and Solutions for the 5th Iteration

Number of Ambulances	Busy Fraction	Ambulance Location Nodes
13	0.6856	5,8,11,15,17,23,27,31,35,51,53,57,62

So the new ambulance locations are not different from the previous ambulance location nodes, so the iteration continues with the response time check obtained in the previous iteration. Confidence interval for the response time is obtained as [12.7446, 13.0278]. Since this interval is greater than the target response time (10 minutes), iterations go on with the update of the number of ambulances, and the next iteration begins.

6th Iteration

Based on the decision obtained from the previous iteration, number of ambulances is increased by one and this 6th iteration continues with scenario 2.5 whose details are given in Table 4.4 in section 4.2.2.3. Parameter settings and the solution of scenario 2.5 are presented in Table 7.10.

Table 7.10. Model Inputs and Solutions for the 6th Iteration

Number of Ambulances	Busy Fraction	Ambulance Location Nodes
14	0.61	5,12,15,17,20,23,27,31,34,36,51,53,57,62

Simulation model is constructed and run for one year, and the outputs for the performance measures (response time, busy fraction and coverage) are analyzed to see the steady state behavior and to determine the truncation point. Moving average graphs are plotted for the three performance measures. These can be seen from Figures 7.8, 7.9, and 7.10.

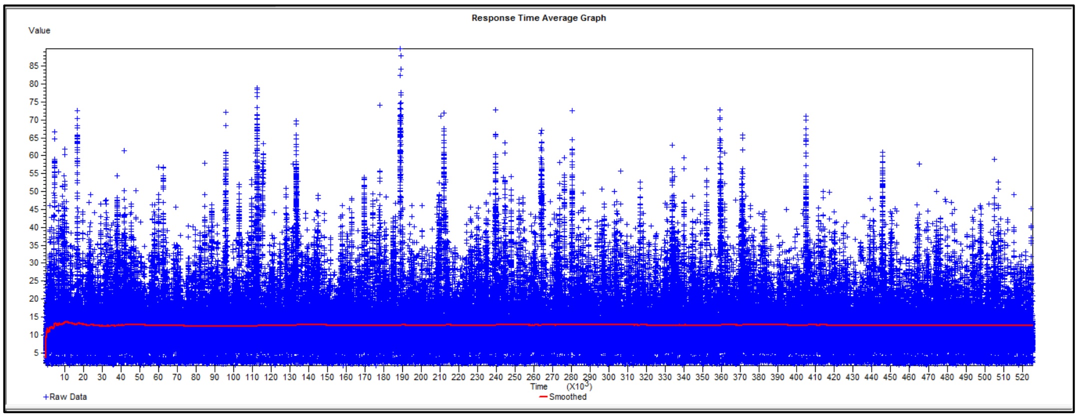

Figure 7.8. Mean Response Time by Simulation Length for the 6th Iteration

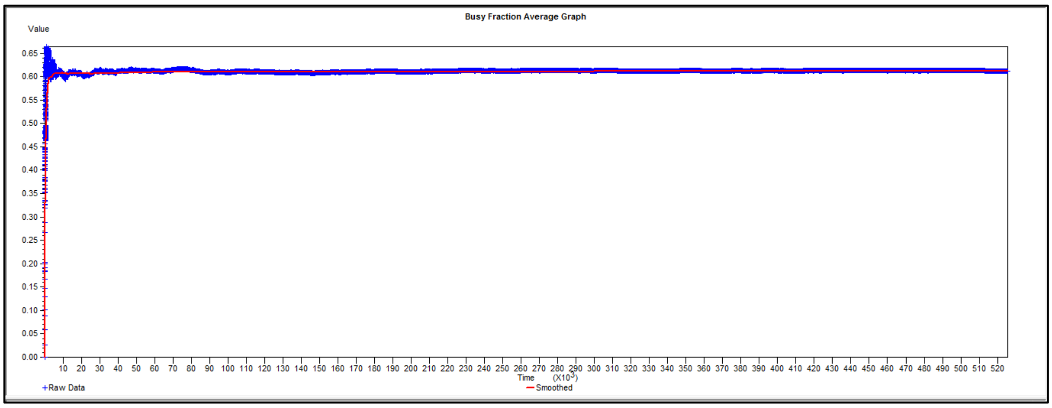

Figure 7.9. Mean Busy Fraction by Simulation Length for the 6th Iteration

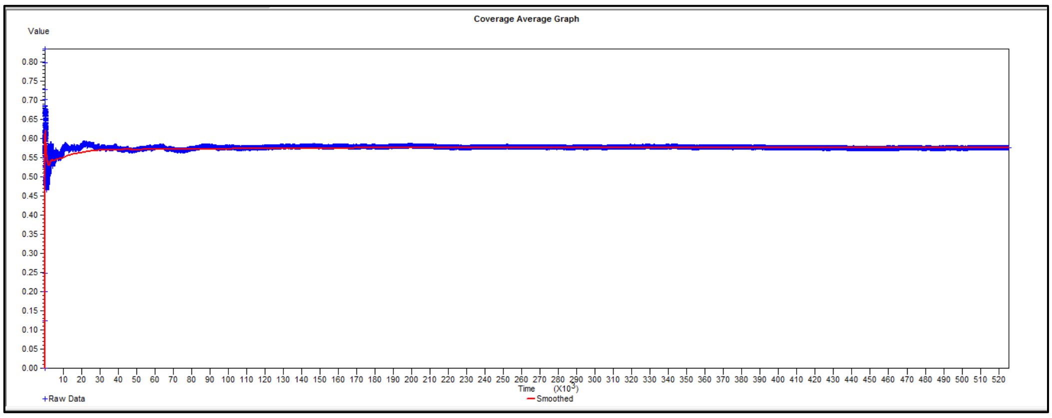

Figure 7.10. Mean Coverage by Simulation Length for the 6th Iteration

According to these graphs, the system reaches the steady state again in 100,000 minutes. Therefore, truncation point and replication length are determined as in the previous iteration. We run the simulation model with 10 replications for the time interval [120,000; 300,000], and construct 95% confidence intervals for all of three performance measures using the replication averages. Confidence intervals are obtained as in Table 7.11.

Table 7.11. 95% Confidence Intervals on Performance Measures for the 6th Iteration

Performance Measure	N	Mean	StDev	SE Mean	95% CI
Busy Fraction	10	0.61099	0.00329	0.00104	[0.60864, 0.61334]
Response Time	10	10.5117	0.1857	0.0587	[10.3789, 10.6445]
Coverage	10	0.57742	0.00535	0.00169	[0.57359, 0.58125]

Results of these initial 10 replications from the output files are as follows:

Precision for busy fraction = $\frac{Half\ Width}{Mean} = \frac{0.00470}{0.61099} = 0.007692 = 0.77\%$

Precision for response time = $\frac{Half\ Width}{Mean} = \frac{0.2656}{10.5117} = 0.02527 = 2.53\%$

Precision for coverage = $\frac{Half\ Width}{Mean} = \frac{0.00776}{0.57742} = 0.013266 = 1.33\%$

These precision values are considered as strong enough; hence, we do not need any more replications to interpret the outputs.

According to the solution approach, the first performance measure that should be analyzed is the busy fraction. Since the initial busy fraction value is found to be 0.61, and it is in this confidence interval, [0.60864, 0.61334], the iteration continues with the response time check. Confidence interval for the response time is obtained as [10.3789, 10.6445], and target response time (10 minutes) is not in this confidence interval. So, iteration goes on by updating the number of ambulances block, and the next iteration begins.

7^{th} Iteration

Based on the decision obtained from the previous iteration, number of ambulances is increased by one, and this 7^{th} iteration continues with the scenario 2.6 in Table 4.4 in section 4.2.2.3 whose parameter settings and solution are as seen in Table 7.12.

Table 7.12. Model Inputs and Solutions for the 7^{th} Iteration

Number of Ambulances	Busy Fraction	Ambulance Location Nodes
15	0.57	5,7,11,15,17,23,27,30,34,36,51,52,57,61,62

Simulation model is constructed and run for one year, and the outputs for the performance measures (response time, busy fraction and coverage) are analyzed to see the steady state behavior and to determine the truncation point. Moving average graphs are plotted for all of the three performance measures. These can be seen in Figures 7.11, 7.12, 7.13.

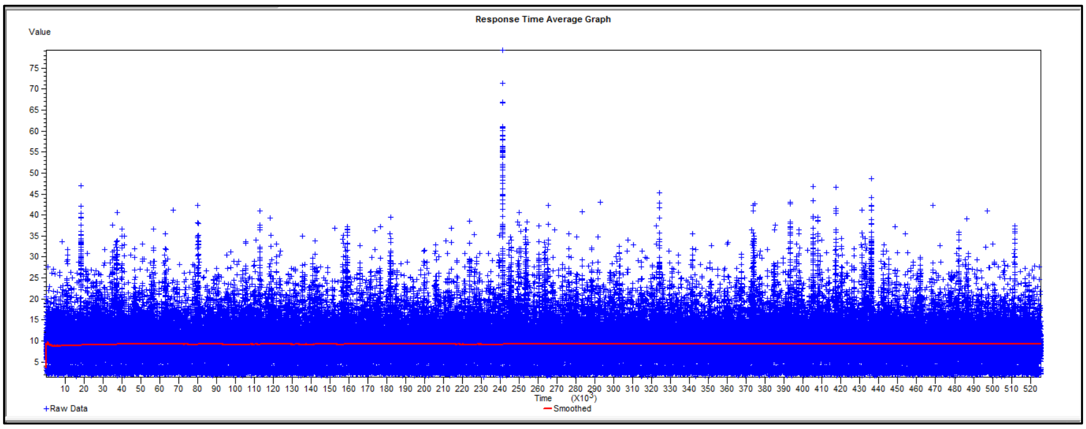

Figure 7.11. Mean Response Time by Simulation Length for the 7th Iteration

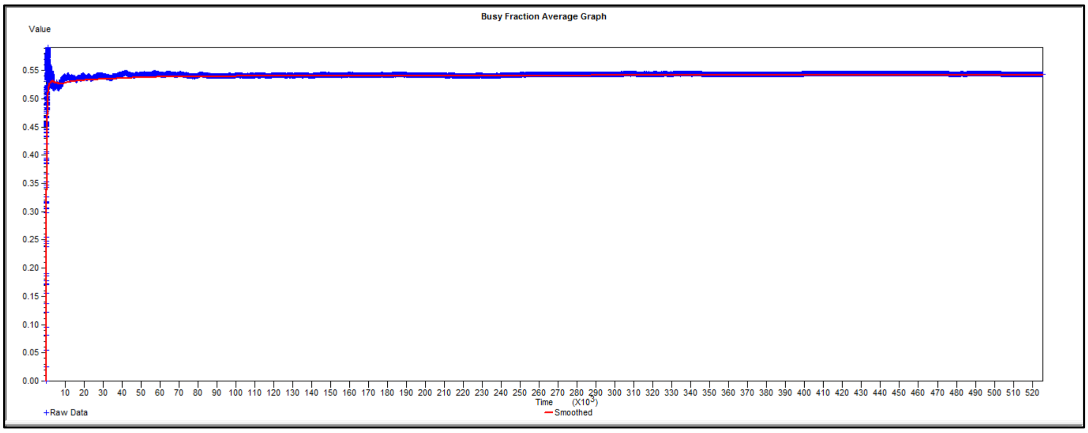

Figure 7.12. Mean Busy Fractions by Simulation Length for the 7th Iteration

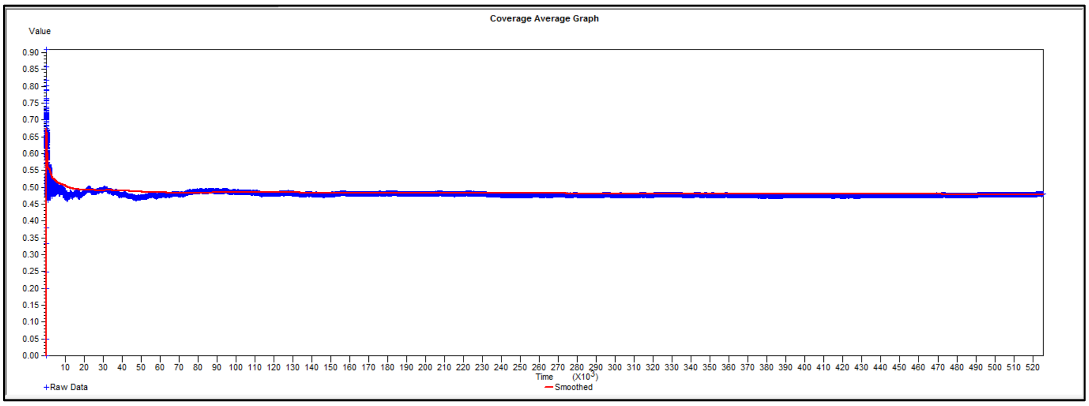

Figure 7.13. Mean Coverage by Simulation Length for the 7th Iteration

According to these graphs, system reaches the steady state, and truncation point and replication length are determined as in the previous iteration. We run the simulation model with 10 replications for the time interval [120,000; 300,000], and construct 95% confidence interval for the three performance measures using the replication averages. Confidence intervals are obtained as in Table 7.13.

Table 7.13. 95% Confidence Intervals on Performance Measures for the 7th Iteration

Performance Measure	N	Mean	StDev	SE Mean	95% CI
Busy Fraction	10	0.5418	0.00327	0.00104	[0.53946, 0.54415]
Response Time	10	9.1716	0.0787	0.0249	[9.1153, 9.2279]
Coverage	10	0.6775	0.0405	0.00128	[0.67459, 0.68039]

Results of these initial 10 replications from the output files are as follows:

Precision for busy fraction = $\frac{Half\ Width}{Mean} = \frac{0.00469}{0.54180} = 0.00866 = 0.87\%$

Precision for response time = $\frac{Half\ Width}{Mean} = \frac{0.1126}{9.1716} = 0.01227 = 1.23\%$

Precision for coverage = $\frac{Half\ Width}{Mean} = \frac{0.0058}{0.6775} = 0.00856 = 0.86\%$

These precision values are strong enough; we do not need any more replications to interpret the outputs.

Since the initial busy fraction value is 0.57 for this number of ambulances, and it is not in this confidence interval, [0.53946, 0.54415], the next iteration begins by updating busy fraction value as 0.5418 to be used in the G-MEXCLP model.

8th Iteration

Based on the decision obtained from the previous iteration, the busy fraction is updated as 0.5418 and this 8th iteration continues with the following parameters in Table 7.14.

Table 7.14. Model Inputs for the 8th Iteration

Number of Ambulances	Busy Fraction
15	0.5418

G-MEXCLP model is reconstructed for these parameters and the ambulance location nodes are obtained as in Table 7.15.

Table 7.15. Model Inputs and Solutions for the 8th Iteration

Number of Ambulances	Busy Fraction	Ambulance Location Nodes	MIP Objective	Solution Time (min)
15	0.5418	5,12,15,17,20,23,27,31,34,36,51,52,57,61,62	11071	8.23

Simulation model is constructed with these ambulance locations and run for one year, and the outputs for the performance measures (response time, busy fraction and coverage) are analyzed to see the steady state behavior and determine the truncation point. Moving average graphs are plotted for the three performance measures. These can be seen in Figures 7.14, 7.15, and 7.16.

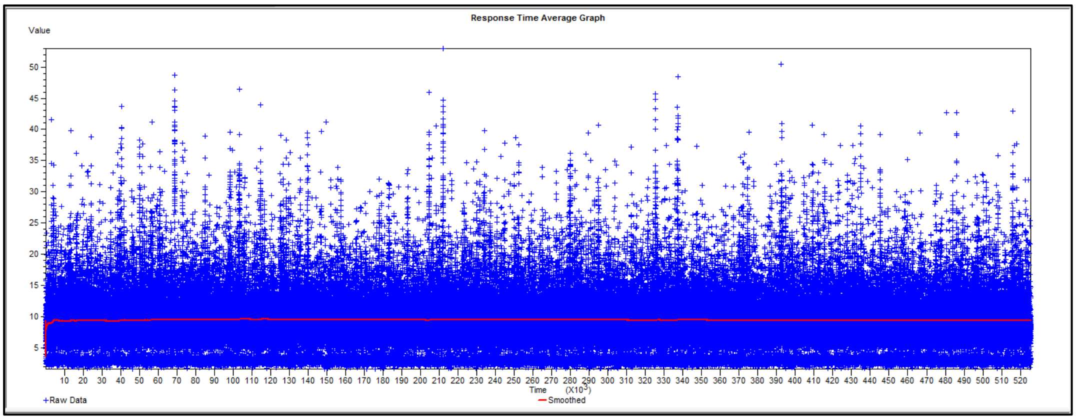

Figure 7.14. Mean Response Time by Simulation Length for the 8th Iteration

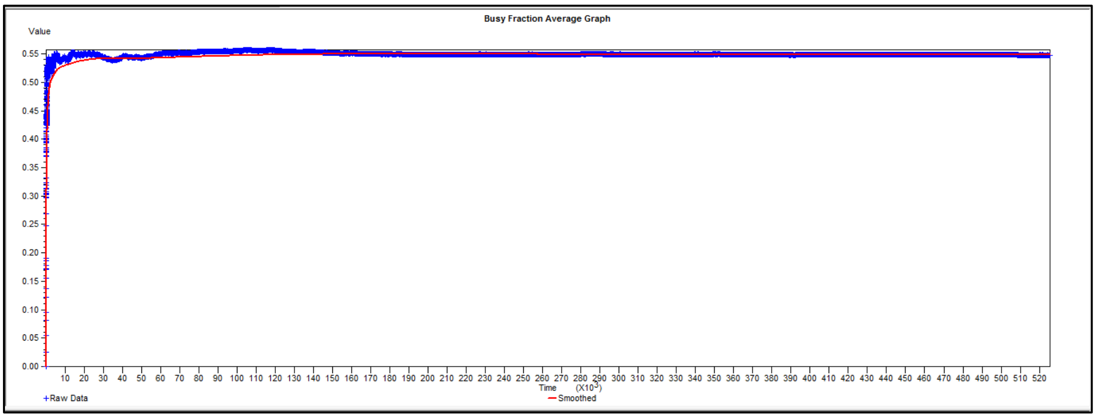

Figure 7.15. Mean Busy Fraction by Simulation Length for the 8th Iteration

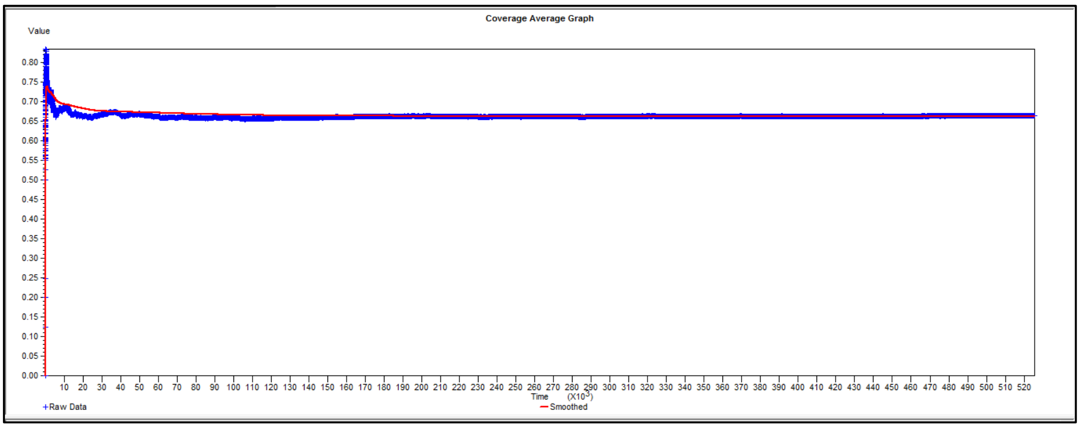

Figure 7.16. Mean Coverage by Simulation Length for the 8th Iteration

According to these graphs, truncation point and replication length can again be determined as 120,000 and 300,000 respectively. We run the simulation model with 10 replications for the time interval [120,000; 300,000], and construct 95% confidence interval for the three performance measures using the replication averages. Confidence intervals are obtained as in Table 7.16.

Table 7.16. 95% Confidence Intervals on Performance Measures for the 8th Iteration

Performance Measure	N	Mean	StDev	SE Mean	95% CI
Busy Fraction	10	0.54651	0.00338	0.00107	[0.54409, 0.54893]
Response Time	10	9.3697	0.0864	0.0273	[9.3078, 9.4315]
Coverage	10	0.6651	0.0423	0.00134	[0.66209, 0.66814]

Results of these initial 10 replications from the output files are as follows:

Precision for busy fraction = $\frac{Half\ Width}{Mean} = \frac{0.00484}{0.54651} = 0.00886 = 0.89\%$

Precision for response time = $\frac{Half\ Width}{Mean} = \frac{0.1237}{9.3697} = 0.01320 = 1.32\%$

Precision for coverage = $\frac{Half\ Width}{Mean} = \frac{0.00605}{0.6651} = 0.00910 = 0.91\%$

These precision values are strong enough; hence, no more replication is needed to interpret the outputs.

Since the busy fraction value used in this iteration is 0.5418, and it is not again in the confidence interval [0.54409 0.54893], the next iteration begins by updating busy fraction value as 0.5465.

9^{th} Iteration

Based on the decision obtained from the previous iteration, busy fraction is updated as 0.5465 and this 9^{th} iteration continues with the following parameters as in Table 7.17.

Table 7.17. Model Inputs for the 9^{th} Iteration

Number of Ambulances	Busy Fraction
15	0.5465

G-MEXCLP model is reconstructed with these parameters and the ambulance location nodes are obtained as in Table 7.18:

Table 7.18. Model Inputs and Solutions for the 9^{th} Iteration

Number of Ambulances	Busy Fraction	Ambulance Location Nodes	MIP Objective	Time (min)
15	0.5418	5,12,15,17,20,23,27,31,34,36,51,52,57,61,62	11043	8.44

So the new ambulance locations are not different from the previous ambulance location nodes, so the iteration continues with the response time check obtained in the previous iteration. Confidence interval for the response time is obtained as [9.3078, 9.4315]. Since this interval is less than the target response time (10 minutes), response time value satisfies the requirements. Hence, iteration continues with the coverage improvement point. Consequently, the next iteration begins with the G-MEXCLP model update once again.

10th Iteration

At this point, response time obtained from the simulation results of iteration 8 is checked for all nodes separately. According to the results (see Table D.1 in Appendix D), average response time of nodes 10, 28 and 63 are 11.1866 minutes, 11.6397 minutes, and 11.0639 minutes, respectively. These are nodes that have the highest response times. Moreover, when we investigate the mathematical model results of the previous iteration and consider each node separately, it is found that the nodes 10, 28 and 63 are covered only at one level. Therefore, the following constraints are added to the mathematical model to improve the demand coverage:

$\sum_{k=1}^{3} y_{10,k} \geq 2$

$\sum_{k=1}^{3} y_{28,k} \geq 2$

$\sum_{k=1}^{3} y_{63,k} \geq 2$

In addition, mandatory coverage constraint is omitted at the same time. So the G-MEXCLP model is solved with this new constraint set, and the following results are obtained as in Table 7.19.

Table 7.19. Model Inputs and Solutions for the 10th Iteration

Number of Ambulances	Busy Fraction	Ambulance Location Nodes	MIP Objective	Time (min)
15	0.5418	2,7,13,14,15,25,27,31,34,40,41,51,57,60,61	10877	5.81

Simulation model is constructed and run for one year, and the outputs for the performance measures (response time, busy fraction and coverage) are analyzed to see the steady state behavior and determine the truncation point. Moving average graphs are plotted in Figures 7.17, 7.18 and 7.19.

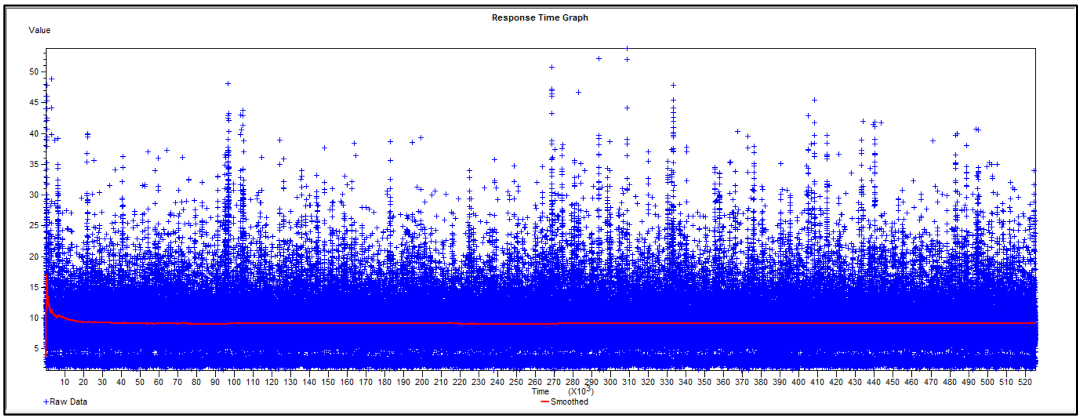

Figure 7.17. Mean Response Time by Simulation Length for the 10th Iteration

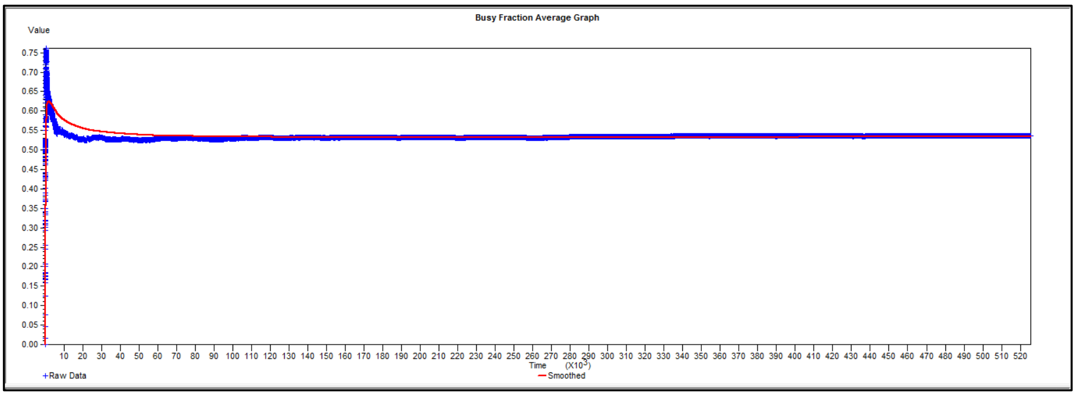

Figure 7.18. Mean Busy Fraction by Simulation Length for the 10th Iteration

According to these graphs, busy fraction and response time reach the steady state at 120,000 minutes, but the system reaches steady state behavior after 250,000 minutes for coverage values. Therefore, this time truncation point is determined as 300,000 minutes and replication length is determined as 480,000 minutes. Statistics for 180,000 minutes are collected for this iteration. 95% confidence interval for the three performance measures are conducted using the replication averages. Confidence intervals are obtained as in Table 7.20.

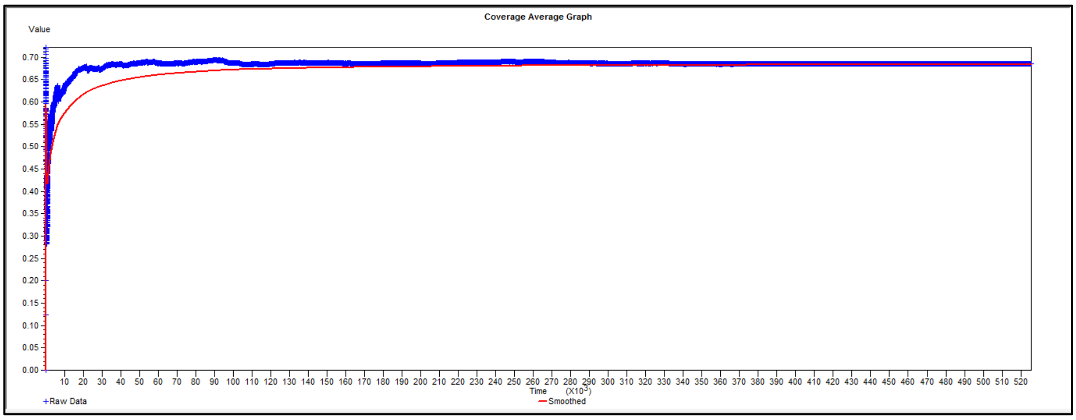

Figure 7.19. Mean Coverage by Simulation Length for the 10th Iteration

Table 7.20. 95% Confidence Intervals on Performance Measures for the 10th Iteration

Performance Measure	N	Mean	StDev	SE Mean	95% CI
Busy Fraction	10	0.53858	0.00296	0.00094	[0.53646, 0.54069]
Response Time (min)	10	9.0959	0.0765	0.0242	[9.0411, 9.1506]
Coverage	10	0.6841	0.00337	0.00107	[0.68166, 0.68648]

Results of these initial 10 replications from the output files are as follows:

Precision for busy fraction = $\frac{\text{Half Width}}{\text{Mean}} = \frac{0.00422}{0.53858} = 0.00785 = 0.79\%$

Precision for response time = $\frac{\text{Half Width}}{\text{Mean}} = \frac{0.1095}{9.0959} = 0.01204 = 1.20\%$

Precision for coverage = $\frac{\text{Half Width}}{\text{Mean}} = \frac{0.00482}{0.6841} = 0.00705 = 0.71\%$

These precision values are strong enough; hence, no more replication is needed to interpret the outputs.

Since the busy fraction value used in this iteration is 0.5418, and it is not again in the confidence interval, [0.53646, 0.54069], the next iteration begins by updating busy fraction value as 0.5386 to be used in the G-MEXCLP model.

11th Iteration

Based on the decision obtained from the previous iteration, busy fraction is updated as 0.5386 and this 11th iteration continues with the following parameters in Table 7.21.

Table 7.21. Model Inputs for the 11th Iteration

Number of Ambulances	Busy Fraction
15	0.5386

G-MEXCLP model is reconstructed for these parameters and the ambulance location nodes are obtained as in Table 7.22.

Table 7.22. Model Inputs and Solutions for the 11th Iteration

Number of Ambulances	Busy Fraction	Ambulance Location Nodes	MIP Objective	Time (min)
15	0.5386	2,7,13,14,15,25,27,31,34,40,41,51,57,60,61	10922	7.11

So the new ambulance locations are not different from the previous ambulance location nodes, so the iteration continues with the response time check obtained in the previous iteration. Confidence interval for the response time is obtained as [9.0411, 9.1506]. Since this interval is less than the target response time (10 minutes), response time value meets the requirements. Therefore, iterations continue with the coverage improvement point.

According to these results, mean coverage has improved to 0.6841 from 0.6651, as was obtained in the previous iterations. Since the results are not the same or worse than the previous iteration, iterations continue with updating the G-MEXCLP model again.

12th Iteration

In this point, response times obtained from the simulation results of iteration 10 is checked for all nodes separately. According to the results (see Table D.2 in

Appendix D), average response time of nodes 20 and 65 are 13.3685 minutes and 11.1308 minutes respectively. These are the nodes that have the highest response times. In addition, the G-MEXCLP model results of the previous iteration are investigated on the basis of each node separately. We see that nodes 20 and 65 are not covered at any level. Therefore, the following constraints are added to G-MEXCLP model developed in the previous level to improve the demand coverage:

$$\sum_{k=1}^{3} y_{20,k} \geq 1$$

$$\sum_{k=1}^{3} y_{65,k} \geq 1$$

The G-MEXCLP model is solved by adding this new constraint set, and the following results are obtained as seen in Table 7.23.

Table 7.23. Model Inputs and Solutions for the 12th Iteration

Number of Ambulances	Busy Fraction	Ambulance Location Nodes	MIP Objective	Time (min)
15	0.5386	3,14,15,17,20,23,25,27,31,34,40,51,57,60,62	10839	7.56

Simulation model is constructed and run for one year, and the outputs for the performance measures (response time, busy fraction and coverage) are analyzed to see the steady state behavior and to determine the truncation point. Moving average graphs are plotted as in Figures 7.20, 7.21, 7.22.

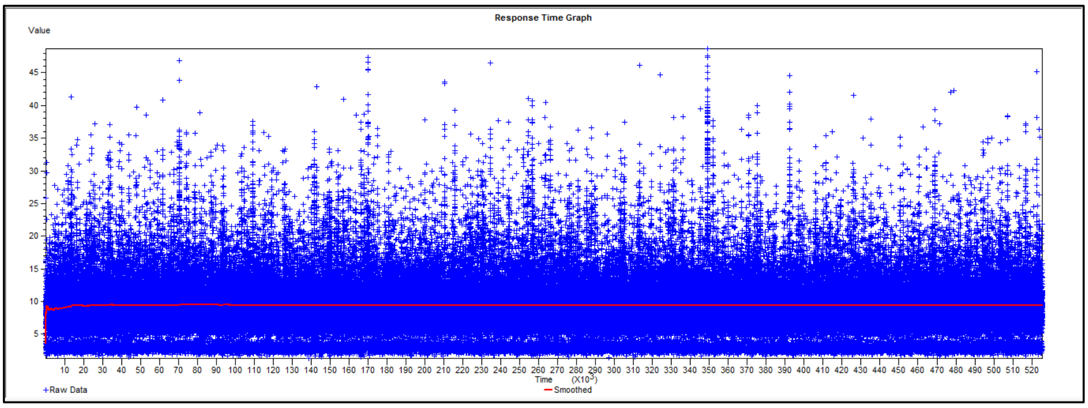

Figure 7.20. Mean Response Time by Simulation Length for the 12th Iteration

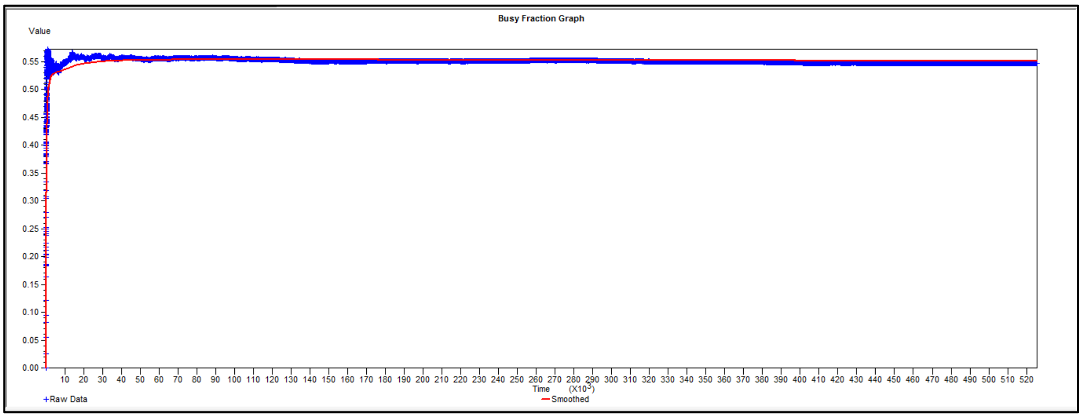

Figure 7.21. Mean Busy Fraction by Simulation Length for the 12th Iteration

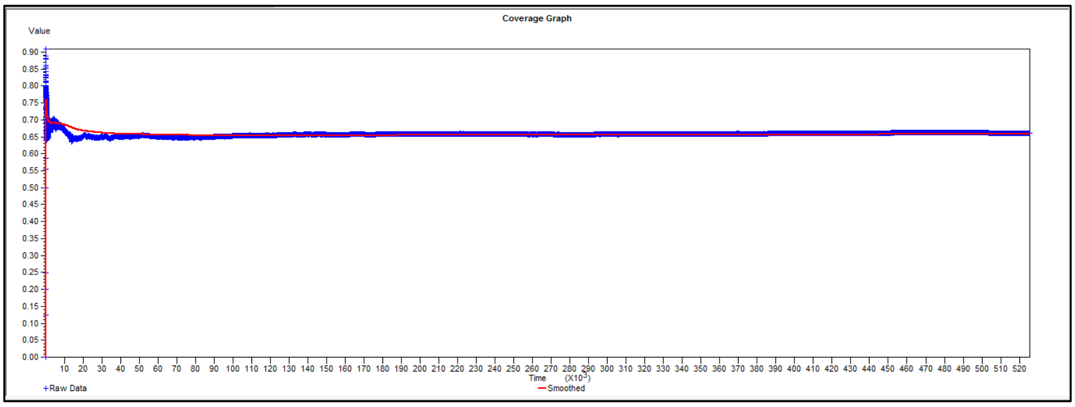

Figure 7.22. Mean Coverage by Simulation Length for the 12th Iteration

According to these graphs, truncation point and replication length can be determined as 120,000 and 300,000 respectively. We run the simulation model with 10 replications for the time interval [120,000; 300,000], and construct 95% confidence intervals for all of three performance measures using the replication averages. Confidence intervals are obtained as in Table 7.24.

Table 7.24. 95% Confidence Intervals on Performance Measures for the 12th Iteration

Performance Measure	N	Mean	StDev	SE Mean	95% CI
Busy Fraction	10	0.54723	0.00386	0.00122	[0.54447, 0.54999]
Response Time	10	9.3158	0.0652	0.0206	[9.2692, 9.3625]
Coverage	10	0.6646	0.00419	0.00133	[0.66157, 0.66756]

Results of these initial 10 replications from the output files are as follows:

Precision for busy fraction = $\frac{\text{Half Width}}{\text{Mean}} = \frac{0.00552}{0.54723}$ = 0.01009 = 1.01%

Precision for response time = $\frac{\text{Half Width}}{\text{Mean}} = \frac{0.0933}{9.3158}$ = 0.01002 = 1.00%

Precision for coverage = $\frac{\text{Half Width}}{\text{Mean}} = \frac{0.00599}{0.6646}$ = 0.00901 = 0.90%

These precision values are strong enough; hence, no more replications are needed to interpret the outputs.

Since the busy fraction value that used in this iteration is 0.5386, and it is not again in the confidence interval, [0.54447, 0.54999]. Therefore, the next iteration begins by updating busy fraction value as 0.5472 to be used in the G-MEXCLP model.

13th Iteration

Based on the decision obtained from the previous iteration, busy fraction is updated as 0.5472 and this 11th iteration continues with following parameters as in Table 7.25.

Table 7.25. Model Inputs for the 13th Iteration

Number of Ambulances	Busy Fraction
15	0.5472

G-MEXCLP model is reconstructed for these parameters and the ambulance location nodes are obtained as in Table 7.26.

Table 7.26. Model Inputs and Solutions for the 13th Iteration

Number of Ambulances	Busy Fraction	Ambulance Location Nodes	MIP Objective	Time (min)
15	0.5472	3,14,15,17,20,23,25,27,31,34,40,51,57,60,62	10786	8.38

So the new ambulance locations are not different from the previous ambulance location nodes, so the iteration continues with the response time check obtained in the previous iteration. Confidence interval for the response time is obtained as [9.2692,9.3625]. Since this interval is less than the target response time (10 minutes), response time value meets the requirements. Therefore, iteration continues with the coverage improvement point.

According to these results, mean coverage decreases to 0.6646 from 0.6841 that was obtained in the previous iterations. Since the results are worse than the previous iterations, iteration terminates at this point; and the last ambulance location plan is accepted. It is as in Table 7.27.

Table 7.27. Model Inputs and Solutions for the 10th Iteration

Number of Ambulances	Busy Fraction	Ambulance Location Nodes	MIP Objective	Time (min)
15	0.5418	2,7,13,14,15,25,27,31,34,40,41,51,57,60,61	10,877	5.81

Finally, at the end of the integrated approach, 15 ambulances are allocated to the nodes, one ambulance for each, 2, 7, 13, 14, 15, 25, 27, 31, 34, 40, 41, 51, 57, 60, 61, and according to this ambulance plan, average response time obtained is 9.0959 minutes, average busy fraction of the ambulances is 53.86%, and the percentage of demand that is reached in 10 minutes is 68.41%. At the same time, 97.92% of the demand is covered in 11 minutes, and 98.61% of the demand is covered in 12 minutes.

7.2. Testing the Current Stations in Adana

In Adana, ambulances currently serve in the 16 active stations in the related districts (Adana 112 İl Ambulans Servisi Başhekimliği), and there are two stations in nodes 6 and 47. However, the total number of ambulances at these stations is not known. According to our solution approach, we suggest 15 ambulances at the last iteration. Therefore, we test the current case in Adana using 15 ambulances assuming there are 2 ambulances in node 6, and 1 ambulance in node 47 in the simulation model to compare our solution and the real case in Adana using the same number of ambulances.

We conduct 10 replications by collecting statistics in the time interval [120,000; 200,000] for the following ambulance locations (Table 7.28).

Table 7.28. Ambulance Locations in the City of Adana

Number of Ambulances	Ambulance Location Nodes
15	2,3,4,6(2),13,21,22,28,40,42,43,47,54,55

We construct 95% confidence intervals for the three performance measures using the replication averages. Confidence intervals are obtained as in Table 7.29.

Table 7.29. 95% Confidence Intervals on Performance Measures for Adana System Simulation

Performance Measure	N	Mean	StDev	SE Mean	95% CI
Busy Fraction	10	0.54414	0.00285	0.0009	[0.54210, 0.54618]
Response Time	10	9.4496	0.0603	0.0191	[9.4065, 9.4928]
Coverage	10	0.6336	0.00386	0.00122	[0.63079, 0.63632]

According to the results in Table 7.30, our solution approach gives better results for all performance measures. Moreover, a major part of demand, 98.6% is covered in, at most, 12 minutes. This is one of our main objectives which is to cover all demand in lower time standards as much as possible, even lower demand areas such as rural areas, as we set the time standards of G-MEXCLP accordingly.

Table 7.30. Comparison Between Our Approach and the Real Case of the City of Adana

Performance Measure	N	City of Adana Mean	Our Approach Mean
Busy Fraction	10	0.54414	0.5386
Response Time	10	9.4496	9.0959
Coverage (10 min)	10	0.6336	0.6841
Coverage (11 min)	10	0.8921	0.9792
Coverage (12 min)	10	0.9426	0.9861

On the other hand, amount of decrease in the performance measures by our approach is thought to be small; however, if we distribute 15 ambulances among nodes randomly as Table 7.31, and investigate the results, simulation results are obtained as in Table 7.32.

Table 7.31. Random Distribution of Ambulances Among the Nodes for the City of Adana

Number of Ambulances	Ambulance Location Nodes
15	1(2),5,10,15,20,25,30,35,40,45,50,55,60,65

Table 7.32. 95% CI on Performance Measures for Random Ambulance Locations

Variable	N	Mean	StDev	SE Mean	95% CI
Busy Fraction	10	0.56333	0.00244	0.00139	[0.56018, 0.5664]
Response Time	10	9.9348	0.0518	0.0164	[9.8978, 9.9719]
Coverage	10	0.5846	0.00538	0.0017	[0.58079, 0.5884]

Thus, according to the characteristic of this data, the decrease obtained by using our solution approach can be considered as significant.

According to the results of computational study on our approach, some modifications can be made in the flow of the iterations. As an example, instead of increasing number of ambulances in the 6th iteration, we might move to the next performance measure check point (coverage improvement) since mean response time value (10.5117 minutes) is very close to the target response time value (10 minutes) in this iteration. Therefore, such modifications can be made in the flow of the solution approach.

CHAPTER 8

CONCLUSION

In this study, briefly, an ambulance location and allocation problem is addressed by an integrated optimization and simulation approach that utilizes both a new mathematical model formulation -G-MEXCLP- and a generic simulation model.

G-MEXCLP model is developed to determine the location of the ambulance stations and the number of ambulances at each station. G-MEXCLP model can be said to be a flexible one in the sense that various preferences of the decision maker can easily be incorporated in the model by adjusting the time standards for successive coverage levels. For example, it can consider all of the demand points as equal as possible, while slightly favoring the high demand points (see also Figures 4.9 and 4.10). On the other hand, these time standards can be set such that, our model G-MEXCLP exactly behaves like MEXCLP, totally favoring high demand points. Several test problems from the literature as well as the real life case of the city of Adana are used to validate and show the characteristics of the G-MEXCLP model.

Our purpose in developing the generic simulation model is twofold. First we intend to improve the G-MEXCLP model in terms of its constraints and parameters, and secondly to test the ambulance location plan obtained in a completely realistic environment, considering all the inherent uncertainties. The most powerful aspect of the simulation model proposed is that it can be used for generic emergency service system problems. In this simulation study, most of the aspects of the ambulance service system are modeled, although some of which are not used in our approach. In the literature, a generic simulation model with substantial detail is not known to the best of our knowledge, despite the fact that many existing studies have been conducted on this topic. Therefore, we choose to provide the detailed modeling information about our simulation model. In addition, simulation model verification and validation are conducted by using the techniques described in sections 5.4.

All in all, in this study, a well-defined integrated approach is proposed to determine the location-allocation of the ambulances as well as a new mathematical model -G-MEXCLP- and a generic simulation model. Our approach can also be considered as a helpful source for developing a decision support system tool for EMS vehicle planning in the future. We test our integrated solution approach on the data for the City of Adana iteratively, and compare the results against the current ambulance plan for the City of Adana. Our approach provides a better solution for all performance measures such as response time, busy fraction and coverage. Moreover, results show that our approach is successful in covering all demand points equally as much as possible with the given time standards of coverage, demonstrating the intended flexibility feature of our model.

As a future research, our approach could be experienced by using some other mathematical models in the literature. If desired, both G-MEXCLP model and simulation model could be structured again to consider different types of calls and different types of ambulances. Moreover, for the larger scale problems that take longer solution times to solve by the G-MEXCLP model, some heuristics can be developed integrating in the solution approach.

REFERENCES

Aboueljinane, L., Sahin, E., & Jemai, Z. (2013). A review on simulation models applied to emergency medical service operations. *Computers and Industrial Engineering, 66*, 734–750.

Acil Sağlık Hizmetleri. (2011). Acil Sağlık Hizmetlerinin Yapısı. Milli Eğitim Bakanlığı, Ankara.

Adana 112 İl Ambulans Servisi Başhekimliği. (2015). Retrieved from http://112.adanasm.gov.tr/Cms.asp?ID=15. [Last accessed on November 12, 2015.]

Alsalloum, O.I., Rand, & G.K. (2003). A goal programming model applied to the ems system at riyadh city, saudi arabia, Working Paper.

Aly, A.A., & White, J.A. (1978). Probabilistic formulation of the emergency service location problem. *Journal of the Operational Research Society, 29,* 1167–1179.

Aringhieri, R., Carello, G., & Morale, D. (2007). Ambulance location through optimization and simulation: the case of Milano urban area. *XXXVIII Annual Conference of the Italian Operations Research Society Optimization and Decision Sciences:*1-29.

Ball, M.O., & Lin, L.F. (1993). A reliability model applied to emergency service vehicle location. *Operations Research, 41*, 18–36.

Batta, R., Dolan, J.M., & Krishnamurty, N.N. (1989). The maximal expected covering location problem: Revisited. *Transportation Science, 23,* 277–287.

Başar, A., Çatay, B., & Ünlüyurt, T. (2012). A taxonomy for emergency service station location problem. *Optimization Letters, 6,* 1147-1160.

Beraldi, P., Bruni, M.E., & Conforti, D. (2004). Designing robust emergency medical service via Stochastic Programming. *European Journal of Operational Research, 158,* 183–193.

Berman, O., Drezner, Z., & Krass, D. (2010). Discrete cooperative covering problems. *Journal of Operational Research Society*. Advance Online Publicating, 15 December 2010.

Brotcorne, L., Laporte, G., & Semet, F. (2003). Ambulance location and relocation models. *European Journal of Operation Research, 147(4),* 451–463.

Christie, P.M.J., & Levary, R.R. (1998). The use of simulation in planning the transportation of patients to hospitals following a disaster. *Journal of Medical Systems, 22,* 289-300.

Church, R.L., & ReVelle, C.S. (1974). The maximal covering location problem. *Papers of the Regional Science Association, 32,* 101–118.

Coşkun, N. (2007). Acil Servis Sistemlerinde Yerleşim Problemlerine Analitik ve Genetik Programlama Yaklaşımları (Master's Thesis), Çukurova Üniversitesi, Adana.

Daskin, M.S. (1983). A maximum expected location model: Formulation, properties and heuristic solution. *Transportation Science, 7,* 48–70.

Daskin, M.S., & Stern, E.H. (1981). A hierarchical objective set covering model for emergency medical service vehicle deployment. *Transportation Science, 15,* 137–152.

Daskin, M.S., Hogan, K., & ReVelle, C. (1988). Integration of Multiple, Excess, Backup, and Expected Covering Models. *Environment and Planning B, 15,* 15-35.

Dessouky, M. (2006). Rapid distribution of medical supplies. In: Patient flow: reducing delay in healthcare delivery. Springer, USA, pp 309–339.

Doerner, K., Gutjahr, W., Hartl, R., Karall, M., & Reimann, M. (2005). Heuristic solution of an extended doublecoverage ambulance location problem for austria. *Central European Journal of Operational Research, 13,* 325–340.

Drezner, T., Drezner, Z., & Goldstein, Z. (2010). A stochastic gradual cover location problem. *Naval Research Logistic, 57,* 367–372.

Erkut, E., Ingolfsson, A., & Erdogan, G., (2007). Ambulance location for maximum survival. *Naval Research Logistic, 55,* 42–58.

Felder, S., & Brinkman, H. (2002). Spatial allocation of emergency medical services: minimising the death rate or providing equal access? *Regional Science and Urban Economics, 32,* 27-45.

Fujiwara, O., Makjamroen, T., & Gupta, K. K. (1987). Ambulance deployment analysis: A case study of Bangkok. *European Journal of Operational Research, 31(1),* 9–18.

Galvao, R.D., Chiyoshi, F.Y., & Morabito, R. (2005). Towards unified formulations and extensions of two classical probabilistic location models. *Computers and Industrial Engineering, 32,* 15–33.

Gendreau, M., Laporte, G., & Semet, F. (1997). Solving an ambulance location model by Tabu search. *Location Science, 5,* 75–88.

Gendreau, M., Laporte, G., & Semet, F. (2001). A dynamic model and parallel Tabu search heuristic for real-time ambulance relocation. *Parallel Computing, 27,* 1641–1653.

Gendreau, M., Laporte, G., & Semet, F. (2006). Themaximal expected coverage relocation problem for emergency vehicles. *Journal of Operational Research Society, 57,* 22–28.

Goldberg, J.B., Dietrich, R., Chen, J.M., Mitwasi, M.G., Valenzuela, T., & Criss, E., (1990). A simulation model for evaluating a set of emergency vehicle base locations: Development, validation, and usage. *Socio-Economic Planning Sciences, 24,* 125-141.

Hogan, K., & ReVelle, C.S. (1986). Concepts and applications of backup coverage. *Management Science, 34,* 1434–1444.

Iannoni, A.P., & Morabito, R. (2007). A multiple dispatch and partial backup hypercube queuing model to analyze emergency medical systems on highways. *Transportation Research, 43,* 755–771.

Ingolfsson, A., Erkut, E., & Budge, S. (2003). Simulation of single start station for Edmonton EMS. *Journal of the Operational Research Society, 54,* 736-746.

Jagtenberg, C.J., Bhulai, S., & van der Mei, R.D. (2015). An efficient heuristic for real-time ambulance redeployment. *Operations Research for Health Care 4,* 27-35.

Jia, H., Ordonez, F., & Dessouky, M.M. (2007). A modeling framework for facility location of medical service for large-scale emergency. *IIE Transactions, 39(1),* 35–41.

Karasakal, O., & Karasakal, E.K. (2004). A maximal covering location model in the presence of partial coverage. *Computers and Industrial Engineering, 31,* 1515–1526.

Karaman, M. (2008). A genetic algorithm for the multi-level maximal covering ambulance location problem (Master's Thesis), Middle East Technical University, Ankara.

Kozan, E., & Mesken, N. (2005). A Simulation Model for Emergency Centres. In Zerger, A & Argent, R (Eds.) Proceedings of the International Congress on Modelling and Simulation. *Advances and Applications for Management and Decision Making,* 12-15 December 2005, Australia, Victoria, Melbourne.

Larson, R.C. (1972). *Urban police patrol analysi*s. The MIT Press, Cambridge, MA.

Li, X., Zhao, Z., Zhu, X., & Wyatt, T. (2011). Covering models and optimization techniques for emergency response facility location and planning: a review. *Mathematical Methods and Operations Research, 74,* 281–310.

Law, A.M., & Kelton, W.,D. (2000). *Simulation Modelling and Analysis*. Third Edition. New York: McGraw-Hill Higher Education.

Lorena, L.A.N., & Pereira, M.A. (2002). A lagrangean/surrogate heurıstıc for the maximal covering location problem using hillsman´s edition. *International Journal of Industrial Engineering - Theory Applications and Practice 9(1),* 57-67.

Maleki, M., Majlesinasab, N., & Sepehri, M.M. (2014). Two new models for redeployment of ambulances. *Computers and Industrial Engineering, 78,* 271-284.

Marianov, V., & ReVelle, C.S. (1995). Siting emergency services. In: Drezner, Z. (Ed.), Facility Location. Springer, New York, pp. 199–223.

Marianov, V., & ReVelle, C. (1996). The queueing maximal availability location problem: a model for the siting of emergency vehicles. *European Journal of Operational Research, 93(1*), 110–120.

Marianov, V., & Serra, D. (1998). Probabilistic maximal covering location allocation models for congested systems. *Journal of Regional Science, 38,* 401–424.

Marianov, V., & Serra, D. (2001). Hierarchical location-allocation models for congested systems. *European Journal of Operational Research, 135,* 195-208.

Marianov, V., & Serra, D. (2002). Location-allocation of multiple-server service centers with constrained queues or waiting times. *Annals of Operations Research, 111,* 35-50.

McLay, L.A. (2009). A maximum expected covering location model with two types of servers. *IIE Transactions*, *41*, 730–741.

Pinto, L.R., Silva, P.M.S., & Young, T.P. (2015). A generic method to develop simulation models for ambulance systems. *Simulation Modelling Practice and Theory*, *51,* 170-183.

Rajagopalan, H.K., Saydam, C., & Xiao, J. (2008). A multiperiod set covering location model for dynamic redeployment of ambulances. *Computers and Industrial Engineering, 35*, 814–826.

Repede, J.F., & Bernardo, J.J. (1994). Developing and validating a decision support system for locating emergency medical vehicles in Louisville, Kentucky. *European Journal of Operational Research*, *75,* 567–581.

RESMİ GAZETE. (11.05.2000). Acil Sağlık Hizmetleri Yönetmeliği. 24046.

ReVelle, C.S., & Hogan, K. (1989a). The maximum availability location problem. *Transportation Science, 23,* 192–200.

ReVelle, C.S., & Hogan, K. (1989b). The maximum reliability location problem and alpha reliable p-center problems: derivatives of the probabilistic location set covering problem. *Annals of Operations Research, 18*, 155–174.

Sanchez-Mangas, R., García-Ferrer, A., de Juan, A., & Arroyo, A.M. (2010). The probability of death in road traffic accidents. How important is a quick medical response? *Accident Analysis and Prevention, 42(4)*, 1048–1056.

Sargent, R.G. (2013). Verification and Validation of Simulation Models. *Journal of Simulation*, *7*, 12-24.

Saydam, C., & Aytug, H. (2003). Accurate estimation of expected coverage: revisited. *Socio-Economic Planning Sciences 37*:69–80.

Schilling, D., Elzinga, D., Cohon, J., Church, RL., & ReVelle, C. (1979). The teem/fleet models for simultaneous facility and equipment sitting,. *Trans Sci 13*:163–175.

Schmid, V., & Doerner, K.F. (2010). Ambulance location and relocation problems with time-dependent travel times. *European Journal of Operational Research, 207(3)*, 1293–1303.

Sorensen, P., & Church, R. (2010). Integrating expected coverage and local reliability for emergency medical services location problems. *Socio-Economic Planning Sciences, 44*, 8-18.

Schneeberger, K., Doerner, K.F., Kurz, A., & Schilde, M. (2014). Ambulance location and relocation models in a crisis. *Central European Journal of Operations Research*, DOI 10.1007/s10100-014-0358-3.

Sullivan, K. (2008). Simulating rural emergency medical services during mass casualty Disasters (Master Thesis). Department of industrial and manufacturing systems engineering, college of engineering Kansas State University.

Toregas, C.R., Swain, R., ReVelle, C.S., & Bergman, L. (1971). The location of emergency service facilities. *Operations Research 19*, 1363–1373.

Wu, C., & Hwank, K.P. (2009). Using a Discrete-event Simulation to Balance Ambulance Availability and Demand in Static Deployment Systems. *Academic Emergence Medicine 16*:1359–1366.

Zhen, Lu., Wang, K., Hu, H., & Chang, D. (2014). A simulation optimization framework for ambulance deployment and relocation problems. *Computers and Industrial Engineering 72*, 12–23.

APPENDIX A

GAMS CODING OF THE MATHEMATICAL MODEL

```
Sets
i/1*323 /
j/1*323/
k/1*5/
;
Parameter
d(i) demand of point i
/
$ondelim
$include Demand.txt
$offdelim
/
p total number of ambulances /12/
q busy probability of ambulances /0.7/
expo(k) exponential of q /1 0 , 2 1 , 3 2 , 4 3 , 5 4/
alpha(k) percent of damand coverage /1 0 , 2 0 , 3 0 , 4 0 , 5 0/
a1(i,j) if demand point i is covered by facility at point j within predetermined time
interval 0<=t<=6 min for k=1
/
$ondelim
$include Aij1.txt
$offdelim
/
a2(i,j) if demand point i is covered by facility at point j within predetermined time
interval 6<t<=9 min for k=2
/
$ondelim
$include Aij2.txt
$offdelim
/
a3(i,j) if demand point i is covered by facility at point j within predetermined time
interval 9<t<=12 min for k=3
/
$ondelim
```

```
$include Aij3.txt
$offdelim
/
a4(i,j) if demand point i is covered by facility at point j within predetermined time
interval 12<t<=15 min for k=4
/
$ondelim
$include Aij4.txt
$offdelim
/
a5(i,j) if demand point i is covered by facility at point j within predetermined time
interval 12<t<=18 min for k=5
/
$ondelim
$include Aij5.txt
$offdelim
/
;
Variables
z total expected demand covered ;
Integer Variables
x(j) number of ambulances located at facility j ;
Binary Variables
y(i,k) if demand point i is covered by at least k times ;
Equations
objective
amb_equilirium1
amb_equilirium2
amb_equilirium3
amb_equilirium4
amb_equilirium5
amb_capacity
demand_percentage
mandatory_coverage ;

objective..           z-sum((i,k),d(i)*(1-q)*(q**(expo(k)))* y(i,k)) =e= 0;
amb_equilirium1(i)..    sum((j),a1(i,j)* x(j)) =g= y(i,'1');
amb_equilirium2(i)..    sum((j),a1(i,j)* x(j))+ sum((j),a2(i,j)* x(j)) =g=  2*y(i,'2');
amb_equilirium3(i)..    sum((j),a1(i,j)* x(j))+ sum((j),a2(i,j)* x(j))+ sum((j),a3(i,j)*
x(j)) =g= 3*y(i,'3');
amb_equilirium4(i)..    sum((j),a1(i,j)* x(j))+ sum((j),a2(i,j)* x(j))+ sum((j),a3(i,j)*
x(j))+ sum((j),a4(i,j)* x(j)) =g= 4*y(i,'4');
amb_equilirium5(i)..    sum((j),a1(i,j)* x(j))+ sum((j),a2(i,j)* x(j))+ sum((j),a3(i,j)*
x(j))+ sum((j),a4(i,j)* x(j))+ sum((j),a5(i,j)* x(j)) =g= 5*y(i,'5');
amb_capacity..         sum(j,x(j)) =l= p  ;                    ;
```

```
demand_percentage(k)..   sum(i,d(i)*y(i,k)) =g= alpha(k)*sum(i,d(i))  ;
mandatory_coverage(i)..  y(i,'1')+y(i,'2')+y(i,'3') =g= 1
;
model MEXCLP/all/;
option optcr=0.01;
option optca=0;
option iterlim = 10000000;
option reslim = 1000000;
option Savepoint=2;
solve MEXCLP using mip maximizing z;
display x.l,y.l,z.l;
```

APPENDIX B

DATA SETS

Table B.1. X-Y Coordinates and Demands of Nodes for Test Data

Node	X Coordinate	Y Coordinate	Demand	Node	X Coordinate	Y Coordinate	Demand
1	409154	435528	50	163	408951	436887	136
2	409151	435683	4	164	409610	434773	16
3	409277	435420	33	165	409638	434867	1
4	409260	435538	15	166	409684	434946	1
5	409240	435695	1	167	409830	435210	24
6	409213	435897	5	168	409738	434678	19
7	409199	435982	87	169	409700	434754	46
8	409178	436078	91	170	409732	434890	30
9	409174	436171	45	171	409718	435043	21
10	409147	436256	1	172	409810	435094	11
11	409469	435389	41	173	409892	435208	33
12	409378	435463	23	174	409968	435327	20
13	409378	435563	26	175	409819	434672	30
14	409351	435734	301	176	409812	434774	43
15	409328	435891	53	177	409823	434877	37
16	409275	435982	1	178	409798	434991	6
17	409289	436065	80	179	409939	435089	51
18	409272	436188	118	180	409972	435164	62
19	409208	436263	1	181	409923	434767	15
20	409754	435326	1	182	409920	434854	8
21	409609	435201	15	183	409892	434941	16
22	409565	435307	12	184	409971	435014	25
23	409577	435510	60	185	410079	435087	37
24	409515	435614	35	186	410064	435263	21
25	409478	435707	138	187	409833	434956	22
26	409442	435810	1	188	410157	435130	25
27	409442	435913	173	189	409962	434875	40
28	409408	436075	61	190	410042	434928	19
29	409344	436201	1	191	410123	434968	27
30	409398	436213	21	192	410197	435045	5
31	409638	435143	8	193	410307	434939	31
32	409683	435349	18	194	410389	434885	17
33	409670	435514	35	195	410230	434688	1
34	409620	435615	17	196	410071	434703	1
35	409688	435618	22	197	410047	434778	1
36	409624	435752	60	198	410113	434847	1
37	409570	435942	65	199	410179	435225	29
38	409541	436090	54	200	410209	435297	42
39	409512	436236	39	201	410244	435175	1
40	409216	435826	1	202	410298	435298	1
41	409158	435820	1	203	410294	435141	26
42	408777	434870	5	204	410347	435267	48

Node	Demand	Node	Demand
51	654	104	25
321	467	120	25
14	301	134	25
54	283	184	25
49	193	188	25
161	185	247	25
27	173	279	25
72	160	294	25
56	153	303	25
75	152	167	24
55	150	254	24
25	138	298	24
163	136	308	24
322	129	12	23
140	127	99	23
301	124	213	23
18	118	287	23
43	115	35	22
67	105	53	22
151	103	121	22
78	102	187	22
45	98	230	22
101	96	281	22
148	96	282	22
156	94	292	22
8	91	30	21
66	90	63	21
127	88	171	21
7	87	186	21
142	84	215	21
149	84	218	21
17	80	261	21
47	79	304	21
68	73	57	20
227	70	137	20
138	67	174	20
37	65	249	20
74	65	262	20
277	64	305	20
52	63	64	19
132	62	87	19
180	62	112	19

Table B.1 (Cont'd)

43	408731	434657	115	205	410359	435086	46
44	408808	434639	30	206	410430	435251	53
45	408840	435022	98	207	410429	435043	58
46	408932	434976	61	208	410511	435237	60
47	408897	434650	79	209	410492	434950	28
48	409050	434674	8	210	410545	435076	6
59	409302	435225	13	221	410660	434732	32
60	409264	435295	3	222	410737	434792	33
61	409452	434831	54	223	410744	435073	30
62	409553	435074	25	224	410808	435074	1
63	409434	435030	21	225	410830	435132	8
64	409517	434818	19	226	410707	434687	28
65	409539	434954	26	227	410780	434673	70
66	409038	435235	90	228	410780	434836	19
67	409167	435416	105	229	410826	434878	16
68	408778	434739	73	230	410894	434903	22
69	409822	435466	1	231	410939	434936	13
70	409811	435545	46	232	410964	434773	38
71	409765	435617	28	233	410816	435249	40
72	409812	435857	160	234	410481	434658	2
73	409792	435978	1	235	410651	434905	1
74	409837	436155	65	236	410783	434971	1
75	409711	436281	152	237	410920	435029	1
76	409969	435509	1	238	411034	435304	1
77	409944	435714	61	239	410556	434848	1
78	410041	435866	102	240	410853	434804	1
79	409946	436015	49	241	410958	434862	1
80	410015	436193	43	242	411037	434936	1
81	410067	435592	1	243	410220	435613	1
82	410073	436039	48	244	410169	435417	26
83	410113	436329	27	245	410228	435388	26
84	410204	436314	6	246	410252	435543	28
85	409645	436119	49	247	410289	435663	25
86	410120	436189	27	248	410348	436049	52
87	409875	435755	19	249	410301	435384	20
88	410180	436398	33	250	410325	435510	30
89	410244	436276	1	251	410345	435646	39
90	410224	436222	1	252	410373	435785	31
91	410435	436784	37	253	410394	435919	30
92	409573	436533	49	254	410417	436035	24
93	409575	436677	54	255	410439	436137	17
94	409553	436813	30	256	410466	436253	18
95	409546	436882	12	257	410395	436240	1
96	409701	436391	34	258	410482	436373	17
97	409691	436539	58	259	410371	435374	11
98	409680	436697	61	260	410394	435496	31
99	409667	436825	23	261	410416	435631	21
100	409657	436892	12	262	410437	435739	20
101	409858	436418	96	263	410468	435817	1
102	409795	436554	37	264	410498	435901	1
103	409788	436708	46	265	410488	436025	17
104	409768	436873	25	266	410507	436128	19
105	409900	436600	52	267	410529	436244	17
106	409863	436728	35	268	410547	436346	11
107	409923	436735	31	269	410430	435369	13
108	409874	436894	41	270	410453	435478	26
109	410006	436607	33	271	410479	435620	19
110	410003	436738	26	272	410502	435734	16

28	61	168	19
46	61	190	19
77	61	228	19
98	61	266	19
23	60	271	19
36	60	296	19
248	52	194	17
179	51	219	17
1	50	255	17
79	49	258	17
85	49	265	17
92	49	267	17
129	49	274	17
82	48	164	16
204	48	183	16
302	48	229	16
293	47	272	16
70	46	273	16
103	46	275	16
169	46	284	16
205	46	4	15
9	45	21	15
80	43	159	15
176	43	181	15
141	42	291	15
200	42	300	14
299	42	59	13
307	42	135	13
11	41	136	13
108	41	231	13
189	40	269	13
233	40	22	12
39	39	95	12
115	39	100	12
118	39	276	12
251	39	172	11
155	38	259	11
232	38	268	11
91	37	306	11
102	37	58	10
146	37	158	9
177	37	31	8
185	37	48	8
119	36	182	8
24	35	225	8
33	35	124	7
106	35	130	7
310	35	317	7
96	34	84	6
139	34	153	6
152	34	178	6
312	34	210	6
3	33	6	5
88	33	42	5
109	33	117	5
126	33	160	5
150	33	192	5
173	33	320	5

Table B.1 (Cont'd)

111	410006	436804	28	273	410551	436010	16
112	409960	436901	19	274	410570	436117	17
113	410014	436903	17	275	410591	436231	16
114	409816	437011	28	276	410606	436337	12
115	410120	436627	39	277	410556	435600	64
116	410099	436799	32	278	410559	435512	18
117	410072	436904	5	279	410580	435727	25
118	410234	436518	39	280	410597	435874	28
119	410205	436634	36	281	410623	435997	22
120	410213	436728	25	282	410646	436100	22
121	410212	436795	22	283	410663	436219	27
122	410320	436562	17	284	410681	436312	16
123	410324	436701	32	285	410593	435427	27
124	410107	437014	7	286	410622	435569	31
125	410201	436904	1	287	410647	435717	23
126	410140	436494	33	288	410675	435867	27
127	409026	436332	88	289	410695	435964	1
128	408906	436537	18	290	410704	436034	1
129	408865	436634	49	291	410718	436100	15
130	408849	436707	7	292	410735	436203	22
131	408791	436841	1	293	410684	435564	47
132	409016	436511	62	294	410709	435710	25
133	408946	436666	26	295	410735	435854	28
134	408921	436738	25	296	410763	435977	19
135	408872	436787	13	297	410778	436090	18
136	408903	436834	13	298	410797	436186	24
137	409160	436346	20	299	410746	435470	42
138	409102	436513	67	300	410735	435556	14
139	409007	436747	34	301	410771	435700	124
140	409261	436338	127	302	410789	435850	48
141	409213	436540	42	303	410812	435963	25
142	409150	436607	84	304	410837	436079	21
143	409114	436740	27	305	410771	435417	20
144	409065	436786	2	306	410805	435484	11
145	409057	436848	18	307	410834	435710	42
146	409174	436708	37	308	410847	435782	24
147	409136	436838	26	309	410883	436197	33
148	409322	436406	96	310	410888	435542	35
149	409255	436694	84	311	410885	435668	32
150	409213	436836	33	312	410895	435848	34
151	409372	436561	103	313	410901	435964	32
152	409286	436828	34	314	410946	435666	1
153	409355	436788	6	315	410955	435841	19
154	409482	436380	31	316	410961	435942	28
155	409456	436520	38	317	411004	435920	7
156	409442	436668	94	318	411002	435664	33
157	409429	436834	32	319	410744	436290	1
158	408514	436845	9	320	408381	434917	5
159	408597	436868	15	321	408392	434637	467
160	408644	436892	5	322	408570	434746	129
161	408796	436835	185	323	408508	434788	5
162	408888	436863	54				

222	33	323	5
309	33	2	4
318	33	50	4
116	32	60	3
123	32	220	3
157	32	144	2
221	32	211	2
311	32	234	2
313	32	5	1
107	31	10	1
154	31	16	1
193	31	19	1
217	31	20	1
252	31	26	1
260	31	29	1
286	31	40	1
44	30	41	1
94	30	69	1
170	30	73	1
175	30	76	1
216	30	81	1
223	30	89	1
250	30	90	1
253	30	125	1
199	29	131	1
71	28	165	1
111	28	166	1
114	28	195	1
209	28	196	1
226	28	197	1
246	28	198	1
280	28	201	1
295	28	202	1
316	28	212	1
83	27	224	1
86	27	235	1
143	27	236	1
191	27	237	1
283	27	238	1
285	27	239	1
288	27	240	1
13	26	241	1
65	26	242	1
110	26	243	1
133	26	257	1
147	26	263	1
203	26	264	1
214	26	289	1
244	26	290	1
245	26	314	1
270	26	319	1
62	25		

Table B.2. Travel Time Between Nodes in Adana Data

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65
1	0	6	7	9	10	12	8	9	12	13	7	8	10	12	14	10	11	12	13	12	7	7	6	8	10	11	13	14	10	8	7	9	9	10	11	12	12	11	13	12	8	9	8	10	9	11	9	11	14	13	10	9	11	12	13	14	13	11	12	12	13	15	14	13	16
2	6	0	7	8	10	12	7	8	10	13	7	7	8	11	12	8	10	12	12	11	9	7	5	7	9	11	11	13	11	9	8	7	8	10	10	11	10	10	11	11	10	10	9	8	8	9	9	9	13	12	11	11	10	11	13	14	14	13	11	11	13	14	15	13	14
3	7	7	0	5	7	9	6	6	7	11	8	8	7	10	11	8	9	9	11	10	10	8	6	7	7	9	10	12	12	11	7	9	6	8	9	10	10	9	9	10	13	11	10	11	10	10	8	10	12	11	13	11	11	11	11	13	15	16	15	12	12	12	16	13	14
4	9	8	5	0	6	9	6	5	7	10	8	7	7	8	10	8	8	9	10	10	12	10	8	7	7	8	10	12	14	12	11	9	7	8	9	10	9	9	9	10	14	12	11	9	9	9	8	9	11	11	14	12	11	11	11	12	17	14	13	11	11	12	17	13	13
5	10	10	7	6	0	7	9	6	5	8	10	9	7	7	7	10	9	10	8	12	13	11	9	8	6	7	8	10	15	15	13	10	9	8	8	9	8	7	8	9	13	14	13	11	9	10	10	11	12	10	15	13	13	12	11	13	17	16	16	12	12	13	18	13	14
6	12	12	9	9	7	0	12	9	7	6	14	12	10	8	7	13	12	11	9	15	13	12	10	9	8	8	9	12	17	15	15	11	10	10	10	10	10	9	10	10	16	15	11	12	12	12	11	12	12	12	19	15	13	12	13	15	20	17	15	14	14	14	20	14	16
7	8	7	6	6	9	12	0	7	8	12	6	6	6	9	9	6	7	8	9	9	10	9	7	8	9	12	13	13	13	12	9	9	9	10	11	11	11	10	11	11	12	12	11	9	10	11	10	11	14	13	13	12	13	12	12	14	16	14	13	13	13	14	17	14	15
8	9	8	6	5	6	9	7	0	6	9	8	7	5	8	9	8	8	9	9	10	11	11	9	7	8	9	10	12	15	13	11	10	8	9	9	10	10	9	9	10	15	14	13	10	10	10	9	10	12	12	15	12	11	11	11	13	16	15	13	12	12	13	18	13	14
9	12	10	7	7	5	7	8	6	0	8	10	9	7	6	7	10	9	10	8	13	13	12	10	8	7	8	8	11	15	15	14	11	9	9	9	10	9	8	8	9	14	14	13	12	10	11	11	11	12	10	16	14	13	13	12	14	17	17	17	13	13	13	19	14	15
10	13	13	11	10	8	6	12	9	8	0	14	13	10	7	6	13	11	10	9	13	16	14	13	11	10	10	11	14	18	18	17	14	12	12	12	13	12	11	11	12	17	17	16	15	13	14	13	14	15	13	18	17	16	15	15	16	20	20	20	15	15	16	22	17	18
11	7	7	8	8	10	14	6	8	10	14	0	5	8	10	12	6	6	9	10	7	13	11	9	11	11	12	13	15	16	14	11	13	9	12	12	13	13	12	12	13	16	14	13	15	13	13	11	13	15	14	17	14	14	14	14	16	19	19	18	15	15	15	19	16	17
12	8	7	8	7	9	12	6	7	9	13	5	0	7	9	10	6	6	8	10	8	12	10	8	10	10	11	12	14	15	13	10	12	8	11	11	12	12	11	11	12	15	13	12	13	12	12	10	12	14	13	16	13	13	13	13	15	18	18	17	14	14	14	18	15	16
13	10	8	7	7	7	10	6	5	7	10	8	7	0	7	8	7	6	8	8	12	12	10	8	10	10	11	12	14	15	13	10	12	8	11	11	12	12	11	11	12	15	13	12	13	12	12	10	12	14	13	15	13	13	13	13	15	17	18	17	14	14	14	18	15	16
14	12	11	10	8	7	8	9	8	6	7	10	9	7	0	6	9	8	8	7	12	15	13	11	10	8	9	10	12	17	17	16	13	11	10	10	11	11	10	10	11	15	16	15	13	12	13	12	13	14	12	17	16	15	14	13	15	19	18	19	14	14	15	20	15	16
15	14	12	11	10	7	7	9	9	7	6	12	10	8	6	0	10	9	7	6	12	16	15	13	11	10	11	11	14	18	18	17	14	12	12	12	13	12	11	11	12	17	17	16	15	13	14	14	14	15	13	19	17	16	16	15	17	20	20	20	16	16	16	22	17	18
16	10	8	8	8	10	13	6	8	10	13	6	6	7	9	10	0	5	7	9	7	13	11	9	10	10	11	13	15	15	14	10	12	9	11	12	13	13	12	12	13	16	14	13	14	12	13	11	13	15	14	16	14	14	14	14	16	18	19	18	15	15	15	19	16	17
17	11	10	9	8	9	12	7	8	9	11	6	6	6	8	9	5	0	6	8	7	13	11	10	11	11	12	13	16	16	15	11	13	10	12	12	13	13	12	13	14	16	15	14	15	13	14	11	13	15	15	17	15	14	14	15	16	19	19	18	15	15	16	19	16	17
18	12	12	9	9	10	11	8	9	10	10	9	8	8	8	7	7	6	0	6	8	14	12	11	12	12	13	14	17	17	15	12	14	11	13	13	14	14	13	14	14	17	16	15	16	14	14	12	14	16	16	18	15	15	15	16	17	20	20	19	16	16	17	20	17	18
19	13	12	11	10	8	9	9	9	8	9	10	10	8	7	6	9	8	6	0	10	13	11	9	11	11	12	13	16	16	14	11	13	10	12	12	13	13	12	13	13	17	15	14	15	13	14	11	13	15	15	17	15	15	14	15	16	19	20	18	15	15	16	20	16	18
20	12	11	10	10	12	15	9	10	13	13	7	8	12	12	12	7	7	8	10	0	15	13	11	13	13	14	15	17	18	16	13	15	11	13	14	15	15	14	14	15	18	16	15	16	15	15	13	15	17	16	19	16	16	16	16	18	21	21	20	17	17	17	21	18	19
21	7	9	10	12	13	13	10	11	13	16	13	12	12	15	16	13	13	14	13	15	0	6	7	8	10	12	13	15	8	6	6	7	9	12	12	12	12	11	13	13	7	7	7	8	9	10	9	10	14	14	8	8	12	11	12	13	11	10	10	10	12	14	12	12	15
22	7	7	8	10	11	12	9	11	12	14	11	10	10	13	15	11	11	12	11	13	6	0	6	7	9	11	11	14	8	7	5	6	8	9	10	11	11	10	11	12	7	8	6	6	7	8	7	8	13	12	9	7	8	10	11	13	11	10	10	9	10	11	12	11	13
23	6	5	6	8	9	10	7	9	10	13	9	8	8	11	13	9	10	11	9	11	7	6	0	6	7	9	10	12	10	9	7	6	6	8	9	9	9	8	9	10	9	9	8	6	7	8	7	8	11	12	10	9	8	9	10	11	13	11	10	10	10	12	14	11	13
24	8	7	7	7	8	9	8	7	8	11	11	10	10	10	11	10	11	12	11	13	8	7	6	0	6	8	9	10	11	10	8	7	5	7	7	8	8	7	7	8	10	10	9	7	8	8	6	7	10	10	12	10	9	10	10	11	14	13	11	10	10	11	15	11	12
25	10	9	7	7	6	8	9	8	7	10	11	10	10	8	10	10	11	12	11	13	10	9	7	6	0	6	7	8	14	12	9	7	6	6	6	6	6	5	5	6	12	11	9	8	7	8	6	7	8	8	13	10	9	9	10	11	14	12	11	10	10	11	15	11	12
26	11	11	9	8	7	8	12	9	8	10	12	11	11	9	11	11	12	13	12	14	12	11	9	8	6	0	5	8	16	14	11	9	8	8	7	8	8	7	6	7	14	12	11	10	9	10	8	9	10	8	15	12	11	11	11	12	15	14	12	12	11	12	17	12	14
27	13	11	10	10	8	9	13	10	8	11	13	12	12	10	11	13	13	14	13	15	13	11	10	9	7	5	0	6	16	14	12	10	8	8	7	7	7	6	5	6	14	13	11	10	9	10	8	9	10	8	15	13	11	11	12	13	16	14	13	12	12	13	17	13	14
28	14	13	12	12	10	12	13	12	11	14	15	14	14	12	14	15	16	17	16	17	15	14	12	10	8	8	6	0	19	17	14	12	11	10	10	10	9	9	8	8	17	15	14	13	12	13	11	12	12	10	18	15	14	14	14	15	18	17	15	15	14	15	20	15	17
29	10	11	12	14	15	17	13	15	15	18	16	15	15	17	18	15	16	17	16	18	8	8	10	11	14	16	16	19	0	6	8	10	11	12	12	13	13	14	14	16	6	8	9	10	11	12	11	12	15	16	6	9	10	13	14	15	8	14	11	11	12	15	10	15	17
30	8	9	11	12	15	15	12	13	15	18	14	13	13	17	18	14	15	15	14	16	6	7	9	10	12	14	14	17	6	0	6	8	10	10	11	12	12	12	12	14	5	6	7	8	10	11	10	10	14	14	7	7	9	10	12	13	9	10	10	10	11	13	11	13	14
31	7	8	7	11	13	15	9	11	14	17	11	10	10	16	17	10	11	12	11	13	6	5	7	8	9	11	12	14	8	6	0	6	8	8	9	10	10	10	10	12	7	6	5	5	7	9	8	8	12	12	8	6	7	8	9	11	11	9	8	8	9	11	12	11	12
32	9	7	9	9	10	11	9	10	11	14	13	12	12	13	14	12	13	14	13	15	7	6	6	7	7	9	10	12	10	8	6	0	9	9	10	11	11	11	12	13	10	10	9	9	8	7	6	7	13	14	11	10	11	9	9	10	14	13	12	10	10	10	14	12	12
33	9	8	6	7	9	10	9	8	9	12	9	8	8	11	12	9	10	11	10	11	9	8	6	5	6	8	8	11	11	10	8	9	0	6	7	8	7	8	8	9	10	9	8	6	6	6	6	8	9	9	10	9	9	9	9	11	13	11	10	9	9	11	14	11	12
34	10	10	8	8	8	10	10	9	9	12	12	11	11	10	12	11	12	13	12	13	12	9	8	7	6	8	8	10	12	10	8	9	6	0	5	5	5	6	6	7	11	10	9	8	6	6	5	6	7	7	12	9	8	7	7	9	12	11	9	8	8	9	15	9	10
35	11	10	9	9	8	10	11	9	9	12	12	11	11	10	12	12	12	13	12	14	12	10	9	7	6	7	7	10	12	11	9	10	7	5	0	5	4	5	6	7	12	11	10	9	6	7	6	6	6	6	12	10	9	8	8	10	13	12	10	9	8	9	16	10	11
36	12	11	10	10	9	10	11	10	10	13	13	12	12	11	13	13	13	14	13	15	12	11	9	8	6	8	7	10	13	12	10	11	8	5	5	0	5	6	6	5	13	12	11	10	7	8	7	7	6	5	13	11	8	6	6	8	12	10	9	8	7	10	14	9	9
37	12	10	10	9	8	10	11	10	9	12	13	12	12	11	12	13	13	14	13	15	12	11	9	8	6	8	7	9	13	12	10	11	7	5	4	5	0	5	5	7	12	11	10	9	7	7	6	7	8	7	13	10	9	8	8	10	13	12	10	9	9	10	16	10	11
38	11	10	9	9	7	9	10	9	8	11	12	11	11	10	11	12	12	13	12	14	11	10	8	7	5	7	6	9	14	12	10	11	8	6	5	6	5	0	5	6	13	12	11	10	8	8	7	8	9	7	14	11	10	9	9	11	14	13	11	10	10	11	17	11	12
39	13	11	9	9	8	10	11	9	8	11	12	11	11	10	11	12	13	14	13	14	13	11	9	7	5	6	5	8	14	12	10	12	8	6	6	6	5	5	0	5	14	13	12	11	9	9	8	9	8	6	15	12	11	10	10	12	15	14	12	11	11	12	18	12	13
40	12	11	10	10	9	10	11	10	9	12	13	12	12	11	12	13	14	14	13	15	13	12	10	8	6	7	6	8	16	14	12	13	9	7	7	5	7	6	5	0	14	13	12	11	9	9	8	9	7	5	14	12	11	10	10	12	15	14	12	11	11	11	18	12	13
41	8	10	13	14	13	16	12	15	14	17	16	15	15	15	17	16	16	17	17	18	7	7	9	10	12	14	14	17	6	5	7	10	10	11	12	13	12	13	14	14	0	5	7	8	10	11	10	11	15	13	6	7	9	9	10	12	8	8	8	9	12	13	11	12	15
42	9	10	11	12	14	15	12	14	14	17	14	13	13	16	17	14	15	16	15	16	7	8	9	10	11	12	13	15	8	6	6	10	9	10	11	12	11	12	13	13	5	0	5	7	9	10	9	9	14	13	6	7	9	10	11	13	8	7	7	8	9	10	10	11	14
43	8	9	10	11	13	11	11	13	13	16	13	12	12	15	16	13	14	15	14	15	7	6	8	9	9	11	11	14	9	7	5	9	8	9	10	11	10	11	12	12	7	5	0	6	8	9	8	8	13	12	7	5	8	9	11	12	9	8	8	8	9	10	11	10	13
44	10	8	11	9	11	12	9	10	12	15	15	13	13	13	15	14	15	16	15	16	8	6	6	7	8	10	10	13	10	8	5	9	6	8	9	10	9	10	11	11	8	7	6	0	6	8	6	7	11	11	8	7	6	7	9	11	10	9	7	7	9	9	12	10	11
45	9	8	10	9	9	12	10	10	10	13	13	12	12	12	13	12	13	14	13	15	9	7	7	8	7	9	9	12	11	10	7	8	6	6	6	7	7	8	9	9	10	9	8	6	0	8	7	7	9	9	13	11	10	9	9	11	14	13	11	10	9	10	17	11	12
46	11	9	10	9	10	12	11	10	11	14	13	12	12	13	14	13	14	14	14	15	10	8	8	8	8	10	10	13	12	11	9	7	6	6	7	8	7	8	9	9	11	10	9	8	8	0	6	5	9	9	10	7	6	5	7	8	11	9	7	7	8	8	12	9	10
47	9	9	8	8	10	11	10	9	11	13	11	10	10	12	14	11	11	12	11	13	9	7	7	6	6	8	8	11	11	10	8	6	6	5	6	7	6	7	8	8	10	9	8	6	7	6	0	6	8	8	11	9	7	7	7	9	13	10	9	8	8	10	13	9	11
48	11	9	10	9	11	12	11	10	11	14	13	12	12	13	14	13	13	14	13	15	10	8	8	7	7	9	9	12	12	10	8	7	8	6	6	7	7	8	9	9	11	9	8	7	7	5	6	0	9	9	11	8	6	6	6	7	11	9	8	7	7	8	12	8	9
49	14	13	12	11	12	12	14	12	12	15	15	14	14	14	15	15	15	16	15	17	14	13	11	10	8	10	10	12	15	14	12	13	9	7	6	6	8	9	8	7	15	14	13	11	9	9	8	9	0	11	15	12	12	11	11	12	16	15	13	12	11	12	19	13	14
50	13	12	11	11	10	12	13	12	10	13	14	13	13	12	13	14	15	16	15	16	14	12	12	10	8	8	8	10	16	14	12	14	9	7	6	5	7	7	6	5	13	13	12	11	9	9	8	9	11	0	15	12	12	10	10	12	15	14	13	11	11	12	18	12	13
51	10	11	13	14	15	19	13	15	16	18	17	16	15	17	19	16	17	18	17	19	8	9	10	12	13	15	15	18	6	7	8	11	10	12	12	13	13	14	15	14	6	6	7	8	13	10	11	11	15	15	0	7	8	9	11	13	7	7	7	9	10	11	8	11	13
52	9	11	11	12	13	15	12	12	14	17	14	13	13	16	17	14	15	15	15	16	8	7	9	10	10	12	13	15	9	7	6	10	9	9	10	11	10	11	12	12	7	7	5	7	11	7	9	8	12	12	7	0	6	7	9	10	8	6	6	7	8	9	9	9	10
53	11	10	11	11	13	13	13	11	13	16	14	13	13	15	16	14	14	15	15	16	12	8	8	9	9	11	11	14	10	9	7	11	9	8	9	8	9	10	11	11	9	9	8	6	10	6	7	6	12	12	8	6	0	5	7	8	10	7	6	5	6	7	10	7	9
54	12	11	11	11	12	12	12	11	13	15	14	13	13	14	16	14	14	15	14	16	11	10	9	10	9	11	11	14	13	10	8	9	9	7	8	6	8	9	10	10	9	10	9	7	9	5	7	6	11	10	9	7	5	0	6	7	11	8	7	5	6	7	11	7	9
55	13	13	11	11	11	13	12	11	12	15	14	13	13	13	15	14	15	16	15	16	12	11	10	10	10	11	12	14	14	12	9	9	9	7	8	6	8	9	10	10	10	11	11	9	9	7	7	6	11	10	11	9	7	6	0	6	12	10	8	6	5	6	13	7	7
56	14	14	13	12	13	15	14	13	14	16	16	15	15	15	17	16	16	17	16	18	13	13	11	11	11	12	13	15	15	13	11	10	11	9	10	8	10	11	12	12	12	13	12	11	11	8	9	7	12	12	13	10	8	7	6	0	12	10	9	7	6	6	13	7	8
57	13	14	15	17	17	20	16	16	17	20	19	18	17	19	20	18	19	20	19	21	11	11	13	14	14	15	16	18	8	9	11	14	13	12	13	12	13	14	15	15	8	8	9	10	14	11	13	11	16	15	7	8	10	11	12	12	0	7	8	9	10	11	6	12	13
58	11	13	16	14	16	17	14	15	17	20	19	18	18	18	20	19	19	20	20	21	10	10	11	13	12	14	14	17	14	10	9	13	11	11	12	10	12	13	14	14	8	7	8	9	13	9	10	9	15	14	7	6	7	8	10	10	7	0	5	7	8	10	7	9	11
59	12	11	15	13	16	15	13	13	17	20	18	17	17	19	20	18	18	19	18	20	10	10	10	11	11	12	13	15	11	10	8	12	10	9	10	9	10	11	12	12	8	7	8	7	11	7	9	8	13	13	7	6	6	7	8	9	8	5	0	6	7	8	8	8	10
60	12	11	12	11	12	14	13	12	13	15	15	14	14	14	16	15	15	16	15	17	10	9	10	10	10	12	12	15	11	10	8	10	9	8	9	8	9	10	11	11	9	8	8	7	10	7	8	7	12	11	9	7	5	5	6	7	9	7	6	0	5	6	8	8	8
61	13	13	12	11	12	14	13	12	13	15	15	14	14	14	16	15	15	16	15	17	12	10	10	10	10	11	12	14	12	11	9	10	9	8	8	7	9	10	11	11	12	9	9	9	9	8	8	7	11	11	10	8	6	6	5	6	10	8	7	5	0	5	12	5	7
62	15	14	12	12	13	14	14	13	13	16	15	14	14	15	16	15	16	17	16	17	14	11	12	11	11	12	13	15	15	13	11	10	11	9	9	10	10	11	12	11	13	10	10	9	10	8	10	8	12	12	11	9	7	7	6	6	11	10	8	6	5	0	14	7	6
63	14	15	16	17	18	20	17	18	19	22	19	18	18	20	22	19	19	20	20	21	12	12	14	15	15	17	17	20	10	11	12	14	14	15	16	14	16	17	18	18	11	10	11	12	17	12	13	12	19	18	8	9	10	11	13	13	6	7	8	8	12	14	0	11	10
64	13	13	13	13	13	14	14	13	14	17	16	15	15	15	17	16	16	17	16	18	12	11	11	11	11	12	13	15	15	13	11	12	11	9	10	9	10	11	12	12	12	11	10	10	11	9	9	8	13	12	11	9	7	7	7	7	12	9	8	8	5	7	11	0	7
65	16	14	14	13	14	16	15	14	15	18	17	16	16	16	18	17	17	18	18	19	15	13	13	12	12	14	14	17	17	14	12	12	12	10	11	9	11	12	13	13	15	14	13	11	12	10	11	9	14	13	13	10	9	9	7	8	13	11	10	8	7	6	10	7	0

Table B.3. Demand of Nodes in the Data for the City of Adana

Sequential Order			
Node	Demand	Node	Demand
1	239	34	185
2	127	35	182
3	175	36	157
4	222	37	144
5	119	38	83
6	156	39	120
7	242	40	209
8	176	41	409
9	350	42	430
10	92	43	361
11	259	44	184
12	162	45	233
13	122	46	188
14	271	47	110
15	48	48	177
16	365	49	11
17	236	50	350
18	93	51	176
19	174	52	107
20	171	53	137
21	105	54	160
22	340	55	131
23	110	56	241
24	232	57	262
25	264	58	48
26	317	59	152
27	292	60	122
28	127	61	131
29	313	62	150
30	284	63	178
31	83	64	71
32	162	65	84
33	151		

Descending Order			
Node	Demand	Node	Demand
42	430	20	171
41	409	12	162
16	365	32	162
43	361	54	160
9	350	36	157
50	350	6	156
22	340	59	152
26	317	33	151
29	313	62	150
27	292	37	144
30	284	53	137
14	271	55	131
25	264	61	131
57	262	2	127
11	259	28	127
7	242	13	122
56	241	60	122
1	239	39	120
17	236	5	119
45	233	23	110
24	232	47	110
4	222	52	107
40	209	21	105
46	188	18	93
34	185	10	92
44	184	65	84
35	182	31	83
63	178	38	83
48	177	64	71
8	176	15	48
51	176	58	48
3	175	49	11
19	174		

APPENDIX C

RESULTS FOR SOME PROBLEM INSTANCES

Table C.1. Results of Scenario 1.3

y_{ik}	1	2	3	4	5
1	1	0	1	1	0
2	1	0	1	1	0
3	1	1	1	1	0
4	1	0	1	1	0
5	1	1	1	1	1
6	0	1	1	1	0
7	1	1	1	0	0
8	0	1	1	1	0
9	0	1	1	1	0
10	0	1	1	1	0
11	1	1	1	1	1
12	1	1	1	1	1
13	1	1	1	1	0
14	1	1	1	1	1
15	1	1	1	1	0
16	1	1	1	0	0
17	1	1	1	0	0
18	1	1	1	1	1
19	1	1	1	1	1
20	1	1	1	1	1
21	1	1	1	1	1
22	1	1	1	1	1
23	1	1	1	1	1
24	1	1	1	1	1
25	1	1	1	1	1
26	1	1	0	1	1
27	1	1	1	1	1
28	1	1	1	1	1
29	1	1	1	1	1
30	1	1	1	1	1
31	1	1	1	1	0
32	1	1	1	1	1
33	1	1	1	1	1
34	1	1	1	1	1
35	1	1	1	1	1
36	1	1	1	1	1
37	1	1	1	1	1
38	1	1	1	1	1
39	1	1	1	1	1
40	1	1	0	1	1

y_{ik}	1	2	3	4	5
109	1	1	1	1	0
110	1	1	1	1	0
111	1	1	1	1	0
112	1	0	1	0	0
113	1	0	0	0	0
114	1	0	0	0	0
115	1	1	0	1	1
116	1	1	0	0	0
117	1	0	0	0	0
118	1	1	0	1	1
119	1	1	0	1	1
120	1	1	0	0	0
121	1	1	0	0	0
122	1	1	1	0	0
123	0	1	0	0	0
124	1	0	0	0	0
125	1	0	0	0	0
126	1	1	0	1	1
127	0	0	1	1	0
128	1	1	0	0	0
129	1	1	0	0	0
130	1	0	0	0	0
131	1	0	0	0	0
132	1	1	1	0	0
133	1	1	0	0	0
134	1	1	0	0	0
135	1	0	0	0	0
136	1	0	0	0	0
137	1	1	1	1	1
138	1	1	1	1	0
139	1	1	0	0	0
140	1	1	1	1	1
141	1	1	1	1	0
142	1	1	1	1	0
143	1	1	0	1	0
144	1	1	0	1	0
145	1	1	0	1	0
146	1	1	1	1	0
147	1	1	0	1	0
148	1	1	1	1	1

y_{ik}	1	2	3	4	5
217	1	1	1	0	0
218	1	1	1	1	0
219	1	1	1	1	0
220	1	1	1	1	0
221	1	0	0	0	0
222	1	0	0	0	0
223	1	1	1	1	0
224	1	1	1	1	0
225	1	1	0	1	0
226	1	0	0	0	0
227	1	0	0	0	0
228	1	0	1	0	0
229	1	0	1	0	0
230	1	0	0	0	0
231	1	0	0	0	0
232	1	0	0	0	0
233	1	1	0	1	0
234	0	1	0	0	0
235	1	1	1	0	0
236	1	0	1	0	0
237	1	0	0	0	0
238	0	1	0	0	0
239	1	1	1	0	0
240	1	0	0	0	0
241	1	0	0	0	0
242	1	0	0	0	0
243	1	0	1	1	1
244	0	1	1	1	1
245	1	1	1	1	1
246	1	0	1	1	1
247	1	1	1	1	1
248	1	1	1	1	1
249	1	1	1	1	1
250	1	0	1	1	1
251	1	1	1	1	1
252	1	1	1	1	1
253	1	1	1	1	0
254	1	1	1	1	1
255	1	1	1	1	1
256	1	1	0	1	0

Table C.1 (Cont'd)

41	1	1	0	1	1
42	1	1	0	0	0
43	1	1	0	0	0
44	1	1	0	0	0
45	1	1	1	1	0
46	1	1	1	1	0
47	1	1	0	0	0
48	1	1	1	0	0
49	1	1	1	1	0
50	1	1	0	0	0
51	1	1	1	1	1
52	1	1	1	1	0
53	1	1	1	1	0
54	1	1	1	1	1
55	1	1	1	1	0
56	1	1	1	1	0
57	1	1	1	1	0
58	1	1	1	1	1
59	1	1	1	1	1
60	1	1	1	1	1
61	1	1	1	1	1
62	1	1	1	1	0
63	1	1	1	1	0
64	1	1	1	1	0
65	1	1	1	1	0
66	1	1	1	1	0
67	1	1	1	1	1
68	1	1	0	0	0
69	0	1	1	1	1
70	0	1	1	1	1
71	0	1	1	1	1
72	1	1	1	1	1
73	1	1	1	1	1
74	1	1	1	1	1
75	1	1	1	1	1
76	0	0	1	1	1
77	0	0	1	1	1
78	0	0	1	1	1
79	0	1	0	1	1
80	1	1	1	1	1
81	0	0	1	1	1
82	1	1	1	1	1
83	1	1	1	1	1
84	1	1	1	1	1
85	1	1	1	1	1
86	1	0	1	1	1
87	0	1	1	1	1
88	1	1	1	1	1
89	1	0	1	1	1
90	1	1	1	1	1
91	0	1	0	0	0
92	1	1	1	1	1
93	1	1	1	1	1
94	1	1	0	1	1

149	1	1	1	1	0
150	1	1	1	1	0
151	1	1	1	1	1
152	1	1	1	1	0
153	1	0	1	1	0
154	1	1	1	1	1
155	1	1	1	1	1
156	1	1	1	1	1
157	1	1	1	1	0
158	1	0	0	0	0
159	1	0	0	0	0
160	1	0	0	0	0
161	1	0	0	0	0
162	1	0	0	0	0
163	1	1	0	0	0
164	1	0	1	1	0
165	1	1	1	1	0
166	1	1	1	1	0
167	1	1	1	1	1
168	0	1	1	0	0
169	1	1	1	1	0
170	1	1	1	1	0
171	1	1	1	1	0
172	1	1	1	1	1
173	1	1	1	1	1
174	0	1	1	1	1
175	0	1	0	0	0
176	0	1	0	0	0
177	1	1	0	1	0
178	1	1	1	1	0
179	1	1	0	1	1
180	1	1	1	1	1
181	1	1	0	1	0
182	1	1	0	1	1
183	1	1	0	1	1
184	1	1	0	1	1
185	1	1	1	1	1
186	1	0	1	1	1
187	1	1	0	1	0
188	1	0	1	1	1
189	1	1	0	1	1
190	1	1	0	1	0
191	1	0	1	1	0
192	1	0	1	1	0
193	1	1	1	1	0
194	1	1	1	1	0
195	1	0	0	1	0
196	1	0	0	0	0
197	1	0	0	1	0
198	1	0	1	1	0
199	1	1	1	1	1
200	1	1	1	1	1
201	1	1	1	1	0
202	1	1	1	1	1

257	1	1	1	1	1
258	1	1	1	1	0
259	1	1	1	1	1
260	1	0	1	1	1
261	1	1	1	1	1
262	1	1	1	1	1
263	1	1	1	0	0
264	1	1	1	0	0
265	1	1	1	0	0
266	1	1	1	1	0
267	1	1	0	1	0
268	1	1	0	1	0
269	1	1	1	1	0
270	1	0	1	1	1
271	1	1	1	1	1
272	1	1	1	1	1
273	1	1	1	0	0
274	1	1	1	1	0
275	1	1	1	1	0
276	0	1	0	1	0
277	1	1	1	1	1
278	1	1	1	1	1
279	1	1	1	1	1
280	1	1	1	0	0
281	1	1	1	0	0
282	1	1	1	0	0
283	1	1	1	0	0
284	1	1	0	1	0
285	1	1	1	1	0
286	1	1	1	1	1
287	1	1	0	1	0
288	1	1	1	0	0
289	1	1	1	0	0
290	1	0	1	0	0
291	1	0	1	0	0
292	1	0	1	0	0
293	1	1	1	1	1
294	1	1	0	1	0
295	1	1	1	1	0
296	1	1	1	0	0
297	1	0	1	0	0
298	1	0	1	0	0
299	1	1	1	1	0
300	1	1	1	1	0
301	1	1	0	1	0
302	1	1	0	1	0
303	1	1	1	0	0
304	1	0	1	0	0
305	1	1	1	1	0
306	1	1	1	1	0
307	1	1	0	1	0
308	1	1	0	1	0
309	1	0	0	0	0
310	1	1	1	0	0

Table C.1 (Cont'd)

95	0	1	0	1	1
96	1	1	1	1	1
97	1	1	1	1	0
98	1	1	1	1	1
99	1	1	0	1	1
100	1	1	0	1	1
101	1	1	1	1	0
102	1	1	1	1	0
103	1	1	1	1	0
104	1	1	1	1	0
105	1	1	1	1	0
106	1	1	1	1	0
107	1	1	1	1	0
108	1	0	1	1	0

203	1	1	1	1	0
204	1	1	1	1	1
205	1	1	1	1	0
206	1	1	1	1	1
207	1	1	1	1	0
208	1	1	1	1	0
209	1	1	1	0	0
210	1	1	1	0	0
211	1	1	1	1	0
212	1	1	1	1	0
213	1	1	1	0	0
214	1	1	1	0	0
215	1	1	1	1	0
216	1	1	0	0	0

311	1	1	1	0	0
312	1	1	0	1	0
313	1	0	0	0	0
314	0	1	1	0	0
315	1	1	0	1	0
316	1	0	0	0	0
317	1	0	0	0	0
318	0	1	0	0	0
319	1	0	0	0	0
320	1	0	0	0	0
321	1	0	0	0	0
322	1	0	0	0	0
323	1	0	0	0	0

Table C.2. Results of Scenario 2.2

y_{ik}	1	2	3	4	5
1	0	1	1	0	1
2	0	0	1	1	1
3	0	1	1	1	1
4	0	1	1	1	1
5	1	1	1	1	1
6	0	0	1	0	0
7	1	1	0	1	1
8	0	0	1	1	1
9	0	1	1	1	1
10	1	0	0	0	0
11	1	1	0	0	0
12	1	1	0	0	1
13	0	0	1	0	1
14	1	0	1	1	1
15	1	0	0	0	0
16	1	1	0	0	1
17	1	1	0	0	0
18	0	1	0	0	0
19	1	0	0	0	0
20	0	1	0	0	0
21	1	1	0	0	0
22	1	1	1	1	1
23	0	1	1	1	1
24	1	1	1	1	1
25	1	1	1	1	1
26	1	1	1	0	0
27	1	1	1	0	0
28	0	0	1	0	0
29	1	0	1	0	0
30	1	1	0	1	0
31	1	1	1	1	1
32	1	1	1	0	1
33	1	1	1	1	1
34	1	1	1	1	1
35	1	1	1	1	1

y_{ik}	1	2	3	4	5
36	1	1	1	1	1
37	1	1	1	1	1
38	1	1	1	0	1
39	1	1	1	0	0
40	1	1	1	0	0
41	1	1	1	1	0
42	1	1	1	1	1
43	1	1	1	1	1
44	1	1	1	1	1
45	0	1	1	1	1
46	1	0	1	1	1
47	1	1	1	1	1
48	1	1	1	1	1
49	0	0	1	0	0
50	1	0	1	0	0
51	1	1	1	1	0
52	1	1	1	1	1
53	1	1	1	1	1
54	1	1	1	1	1
55	1	1	0	0	1
56	1	0	0	0	0
57	1	0	0	0	0
58	0	1	1	1	1
59	1	0	1	1	1
60	1	1	1	1	1
61	1	1	0	0	1
62	1	1	0	0	0
63	1	0	0	0	0
64	0	1	0	0	0
65	1	0	0	0	0

APPENDIX D

AVERAGE RESPONSE TIME FOR SOME SIMULATION RUNS

Table D.1. Average Response Time of the Simulation Results for Iteration 8

Node	Average Response Time	Node	Average Response Time
1	10.3888	34	7.8316
2	10.0329	35	8.9438
3	9.8517	36	7.3750
4	9.9208	37	9.1240
5	8.3508	38	9.4209
6	10.8535	39	9.3322
7	9.8206	40	9.5527
8	10.0362	41	9.9966
9	9.7971	42	9.6090
10	11.1866	43	9.0317
11	9.3626	44	9.4318
12	7.6192	45	9.9152
13	9.7502	46	9.8657
14	10.2314	47	9.5301
15	7.9507	48	9.7618
16	9.3175	49	9.8519
17	7.5029	50	10.0596
18	10.1937	51	7.9195
19	10.3243	52	7.7987
20	7.1807	53	9.2469
21	10.3304	54	9.1638
22	9.5241	55	8.5534
23	8.2707	56	9.5434
24	9.7094	57	7.2701
25	9.3384	58	10.0788
26	9.7506	59	9.8591
27	8.0648	60	8.4954
28	11.6397	61	6.8739
29	10.6094	62	6.4288
30	10.2186	63	11.0639
31	8.1709	64	9.5754
32	10.4881	65	10.3494
33	9.3925		

Table D.2. Average Response Time of the Simulation Results for Iteration 8

Node	Average Response Time	Node	Average Response Time
1	10.0945	34	7.4676
2	7.8020	35	8.9931
3	9.5750	36	8.4377
4	9.5024	37	9.0594
5	9.5213	38	8.8243
6	10.3963	39	8.5591
7	7.7627	40	7.2148
8	9.3908	41	7.6828
9	9.2767	42	8.7980
10	10.0592	43	9.2059
11	10.5762	44	9.1874
12	9.9854	45	9.5975
13	7.2710	46	9.6240
14	6.9750	47	9.0954
15	6.9983	48	9.4086
16	10.1354	49	10.8130
17	9.9921	50	9.5238
18	10.4270	51	6.8550
19	9.8680	52	9.5625
20	13.2132	53	8.7279
21	9.9374	54	8.9093
22	9.3547	55	9.0364
23	8.9683	56	10.2858
24	9.5270	57	6.6933
25	7.4293	58	9.8359
26	8.9748	59	9.4387
27	7.0532	60	6.6769
28	10.6535	61	6.9130
29	9.6950	62	9.5305
30	9.0323	63	10.3309
31	7.7562	64	9.5446
32	9.8353	65	11.0314
33	9.3524		

APPENDIX E

DATA SET FOR SIMULATION VERIFICATION

Table E.1. Average Travel Time Between Nodes

Index	TravelTimeMatrix					
1	1.5	3	6	9	12	15
2	3	1.5	3	6	9	12
3	6	3	1.5	3	6	9
4	9	6	3	1.5	3	6
5	12	9	6	3	1.5	3
6	15	12	9	6	3	1.5

Table E.2. Ambulance and Hospital Matrix, Demand Probabilities

Index	AmbMatrix	HospitalMatrix	DemandProbMatrix
1	1	0	0.2
2	1	1	0.1
3	0	0	0.1
4	0	0	0.1
5	2	1	0.4
6	0	0	0.1

APPENDIX F

VARIABLES AND ATTRIBUTES LIST

Table F.1. Variable List of the Simulation Model and Initial Values for Adana Data Set

Name	Rows	Columns	File Name	File Read Name	Initial Values
InterArrivalTime	Real	System		BeginReplication	3.523
pAmbNeeded	Real	System		BeginReplication	1
TotalNoOfLocations	Real	System		BeginReplication	65
CCPerformingTimeMean	Real	System		BeginReplication	2
CCPerformingTimeVariance	Real	System		BeginReplication	0.5
pSeverity2	Real	System		BeginReplication	0
pSeverity1	Real	System		BeginReplication	1
TotalNoOfAmbs	Real	System		BeginReplication	15
NoOfAvailableAmbs	Real	System		BeginReplication	15
AmbMatrix	65	1	ExtSimDataFile	BeginReplication	
HospitalMatrix	65	1	ExtSimDataFile	BeginReplication	
TravelTimesMatrix	65	65	ExtSimDataFile	BeginReplication	
BusyFraction	Real	System		BeginReplication	
TotalAmbUsage	Real	System		BeginReplication	
pHospitalNeeded	Real	System		BeginReplication	0.34
AmbSetupTimeMean	Real	System		BeginReplication	2
AmbSetupTimeVariance	Real	System		BeginReplication	0.5
TimeAtSceneAlpha	Real	System		BeginReplication	1.2
TimeAtSceneBeta	Real	System		BeginReplication	7.5
TimeAtSceneThreshold	Real	System		BeginReplication	1
TimeAtHospitalAlpha	Real	System		BeginReplication	1
TimeAtHospitalBeta	Real	System		BeginReplication	4
TimeAtHospitalThreshold	Real	System		BeginReplication	1
TargetResponseTime	Real	System		BeginReplication	10
TestInterrupt	Real	System		BeginReplication	
CoveredDemand	Real	System		BeginReplication	
Coverage	Real	System		BeginReplication	
TotalNoOfCalls	Real	System		BeginReplication	
ResponseTimeMatrix	65	1		BeginReplication	
CallCountMatrix	65	1		BeginReplication	

Table F.2. Attribute List of the Simulation Model

Name
StartTime
CallType
CallLocation
Severity
TimeToEnterQueue
AssignedStation
Index
ResponseTime
DispatchTime
AmbUsageTime
CallResolveTime
AssignedHospital

APPENDIX G

DATA SET FOR SIMULATION VERIFICATION AND VALIDATION

Table G.1. Ambulance and Hospital Matrix

AmbulanceMatrix				HospitalMatrix			
1	0	35	0	1	0	35	0
2	1	36	0	2	0	36	0
3	0	37	0	3	0	37	0
4	0	38	0	4	0	38	1
5	0	39	0	5	0	39	0
6	0	40	1	6	0	40	0
7	1	41	1	7	0	41	0
8	0	42	0	8	1	42	0
9	0	43	0	9	0	43	0
10	0	44	0	10	0	44	0
11	0	45	0	11	0	45	0
12	0	46	0	12	0	46	0
13	1	47	0	13	0	47	0
14	1	48	0	14	0	48	0
15	1	49	0	15	0	49	0
16	0	50	0	16	0	50	0
17	0	51	1	17	0	51	0
18	0	52	0	18	0	52	0
19	0	53	0	19	0	53	0
20	0	54	0	20	0	54	0
21	0	55	0	21	0	55	1
22	0	56	0	22	1	56	0
23	0	57	1	23	0	57	0
24	0	58	0	24	0	58	0
25	1	59	0	25	0	59	0
26	0	60	1	26	0	60	0
27	1	61	1	27	0	61	0
28	0	62	0	28	0	62	0
29	0	63	0	29	0	63	0
30	0	64	0	30	0	64	0
31	1	65	0	31	0	65	0
32	0			32	0		
33	0			33	0		
34	1			34	0		