



**MARMARA UNIVERSITY
INSTITUTE FOR GRADUATE STUDIES
IN PURE AND APPLIED SCIENCES**



**DEVELOPMENT OF HEURISTIC OPTIMIZATION METHODS AND
EXPERIMENTAL SIMULATION DESIGN FOR THE COMPONENTS AND
RESOURCES OF HEALTHCARE**

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Ph.D. THESIS

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ISTANBUL, 2019

**MARMARA UNIVERSITY INSTITUTE FOR GRADUATE
STUDIES IN PURE AND APPLIED SCIENCES**

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dedicated to my wife and daughters

Patient is not a customer!

Abstract

Development of Heuristic Optimization Methods and Experimental Simulation Design for the Components and Resources of Healthcare

Healthcare is one of the largest and fastest growing businesses besides manufacturing. Most of the countries, especially the U.S. do not have a global or local healthcare system but have a unique and complex system for healthcare service and delivery. This complexity causes many problems such as poor-quality service, duplicates, wrong treatment, high waiting time, medication error, etc. In health systems around the world, there are two types of problems that belong to health institutions. First, the waiting times for treating patients in public health facilities are very high. For this reason, patient dissatisfaction and state health spending are increasing disproportionately. The second problem belongs to private health institutions. In such health institutions, the waiting time of the patients is low, but the cost of the treatment is high. This means that patients have to pay a lot of money from their pocket to wait less. Because of this, the number of patients treated annually in private health institutions is decreasing and their annual income is decreasing. In order to solve such problems positively, the use of optimization method which is mathematical modelling is inevitable. This thesis consists of three chapters.

There are two structures in healthcare system worldwide; these are public and private healthcare systems. There are many components that built up health systems. Especially, patients, governments as the main rules and laws maker for health care, healthcare providers and private healthcare sectors (private healthcare insurance companies, private hospitals, resources of private healthcare) are at the center of the healthcare system. In the section that constitutes the first part of the thesis, optimization models are developed by comparing healthcare systems both at the monopoly level and interactively. Intuitive mathematical models developed for health systems aim to achieve optimum results.

The second part of the thesis is related to the management of healthcare resources. The aim of this research is to apply discrete event simulation approach based on optimization modelling and design of experiment (DOE) technique to derivate strategies and analyze

situations to find optimum solutions in a healthcare department. Since healthcare systems have a stochastic structure, mathematical modeling is usually expressed by closed formulas. It is common to use simulation techniques of systems that cannot be mathematically modeled explicitly. However, with this study, the scenarios of the resources were created, and intuitive mathematical models were developed for each situation. Thus, the objectives of these applications are the minimization the waiting time of the patients, and the maximization the number of treated patients. In addition to this section, a simulation model to reduce the density of the emergency service with advanced nurses employed in the emergency services have been developed in Turkey.

In the third chapter, the quality of health systems of countries is questioned. A statistical optimization model has been developed to create a global healthcare competitiveness index (GHCI) covering 53 countries with a gross domestic product per capita of over US \$ 10,000. GHCI determines the ease or difficulty of receiving services for patients from healthcare systems of considered countries. Factors considered to be influential on the GHCI were identified and significance levels were analyzed statistically. Then, the desirability equation that is formed in the factors has been established to form the objective function in the optimization model. This section of the thesis has determined the optimum values of the factors for countries to be able to compete in healthcare service. Having those factors with optimum values is an indicator of higher quality of healthcare systems.

According to the data obtained through the developed methods, the best solutions were obtained by comparing the scenarios and criteria for the decision variables within the healthcare system. In all three parts of the thesis, all the components included in the healthcare system are benefited with the results obtained by this research. It is aimed that the patient factor is addressed in the center of healthcare systems was benefit more.

Keywords: Public Healthcare System, Private Healthcare System, Heuristic Optimization Models, Design of Experiment, Simulation, Advanced Nurse, Global Health Competitiveness Index

Özet

Sağlık Bileşenleri ve Kaynakları için Sezgisel Optimizasyon Yöntemlerinin ve Deneysel Simülasyon Tasarımının Geliştirilmesi

Sağlık sektörü, üretim dışında en büyük ve en hızlı büyüyen sektörlerden biridir. Çoğu ülkede, özellikle ABD’de küresel veya yerel bir sağlık sistemi bulunmamakla birlikte, sağlık hizmetleri için benzersiz ve karmaşık bir sistem bulunmaktadır. Bu karmaşıklık, kalitesiz hizmet, duplikasyonlar, yanlış tedavi, yüksek bekleme süresi, ilaç hatası vb. gibi birçok soruna neden olmaktadır. Dünyada var olan sağlık sistemlerinde, sağlık kuruluşlarına ait iki tür sorun vardır. Birincisi, devlet sağlık kuruluşlarında hastaların tedavi olmak için bekleme süreleri çok yüksektir. Bu nedenle hasta memnuniyetsizliği ve devlet sağlık harcamaları orantısız bir şekilde artmaktadır. İkinci problem ise özel sağlık kurumlarına aittir. Bu tür sağlık kuruluşlarında hastaların bekleme zamanı düşüktür ancak hastanın ödeyeceği tedavi maliyeti yüksektir. Bu, hastaların daha az beklemek için cebinden daha çok para ödemeleri gerektiği anlamına gelmektedir. Bu nedenle özel sağlık kurumlarında yıllık tedavi edilen hasta sayısı azalmaktadır ve yıllık gelirleri düşmektedir. Bu tür problemleri çözmek için iyi tanımlanmış matematiksel modelleme ile mantıklı bir çözüm elde etmek için optimizasyon yöntemi olarak bilinen sezgisel bir metot kullanımı kaçınılmaz olmaktadır.

Dünyada sağlık sisteminde iki yapı vardır; bunlar devlet ve özel sağlık sistemleridir. Sağlık sistemlerini oluşturan birçok bileşenler bulunmaktadır. Özellikle hastalar, devletler (sağlık hizmetleri için ana kuralları ve yasaları yapan), sağlık hizmeti verenler ve özel sağlık sektörleri (özel sağlık sigorta şirketleri, özel hastaneler, özel sağlık sektörü çalışanları) sağlık sisteminin merkezinde yer almaktadır. Bu tez üç ana kısımdan oluşmaktadır. Tezin ilk kısmını oluşturan bölümde, sağlık sistemleri hem tekel düzeyde hem de etkileşimli olarak ele alınması ile optimizasyon modelleri geliştirilerek karşılaştırma yapılmıştır. Sağlık sistemleri için geliştirilen sezgisel matematiksel modellerde optimum sonuçların elde edilmesi amaçlanmıştır.

Tezin ikinci bölümü ise sağlık hizmeti veren kuruluşlara ait sağlık kaynaklarının yönetimi ile alakalıdır. Stratejiler geliştirilerek sağlık sistemlerine ait kaynakların optimum sayısını elde etmek için deney tasarımı (DOE) tekniğinden yararlanılarak kesikli-olay-simülasyon modellemesi yapılmıştır. Sağlık sistemleri stokastik bir yapıya sahip oldukları için genellikle matematiksel modeller kapalı formüller ile ifade edilmektedir. Açıkça matematiksel olarak modellenemeyen sistemlerin simülasyon tekniklerini kullanmak

yaygındır. Ancak, bu çalışma ile kaynaklara ait senaryolar oluşturularak her bir durum için sezgisel matematiksel modellemeler geliştirilmiştir. Böylelikle, hastaların bekleme süreleri en aza indirilerek tedavi edilen hastaların sayısını maksimuma çıkarılması amaçlanmıştır. Bu bölüme ek olarak, Türkiye’deki acil servislerinde uzman hemşire istihdamı ile acil servislerdeki yoğunluğun azaltılmasına yönelik bir simülasyon modeli geliştirilmiştir.

Üçüncü bölümde, ülkelere ait sağlık sistemlerinin kalitesi sorgulanmıştır. Kişi başına düşen gayri safi milli hasılası 10.000 ABD dolarını aşan 53 ülkeyi kapsayan bir küresel sağlık rekabet endeksini (GHCI) oluşturmak için istatistiksel optimizasyon modeli geliştirilmiştir. Bu çalışmada, GHCI hastaların sağlık kuruluşlarında hizmet alma kolaylığını veya zorluğunu belirten bir indeks olarak tanımlanmıştır. GHCI üzerinde etkili olduğu düşünülen faktörler belirlenmiş ve anlamlılık düzeyleri istatistiksel olarak analiz edilmiştir.

Geliştirilen yöntemler aracılığıyla elde edilen verilere göre sağlık sisteminin içinde yer alan karar değişkenleri için senaryolar ve kriterler karşılaştırılarak en iyi çözümler elde edilmiştir. Tezin her üç kısmında, elde edilen sonuçlar ile sağlık sisteminin içinde yer alan bütün bileşenlerin fayda görmesi sağlanmıştır. Sağlık sistemlerin merkezinde yer alan "hasta" faktörünün daha çok fayda görmesi hedeflenmiştir

Anahtar Kelimeler: Devlet Sağlık Sistemi, Özel Sağlık Sistemi, Sezgisel Optimizasyon Modeli, Deney Tasarımı, Simülasyon, Uzman Hemşire, Küresel Sağlık Rekabet İndeksi

Claim of Originality

In writing this thesis, the most important element that triggers me is the quality of healthcare of people. This thesis is important because patients cannot be referred to as customers. Having healthcare service is a social right for people. I advocate that this social right cannot be sold with money. I wrote this thesis to ensure that people get maximum healthcare service with minimum cost. I wanted to ensure that the best results are obtained by taking care of the rights of the patients in the center of the health systems.

The fastest growing area in the world after the production is the health sector. Many countries, especially USA, regard the healthcare sector as a business. This situation brings to the highest level the concept of competition in terms of economy and quality in healthcare sector. In this research, it has been aimed to increase the incomes of private health institutions and to reduce the costs in the state health system. These new methods developed has been studied for the first time in this thesis and tangible results have been obtained in the field of healthcare.

This thesis consists of three chapters. The first part of the thesis contains heuristic optimization models developed for public and private health systems. Objective functions have been defined for each healthcare systems. The objective function of the public healthcare system is to minimize the costs (break-even; non-profit-organization) and reduce the patient waiting time while the objective of the private healthcare system is to increase the number of patients who are treated and increase their income. In the second chapter, heuristic optimization models were developed by using design of experiment and simulation technique for the proper management of healthcare resources belonging to public or private healthcare providers. In addition to this section, a simulation model to reduce the density of the emergency service with advanced nurses employed in the emergency services have been developed in Turkey. In the third chapter, a global healthcare competitiveness index was established to measure the quality of healthcare systems belonging to the states. To create this index, a mathematical model was developed using desirability method. In all three chapters, the methods developed for this thesis will contribute to science as an innovation.

February 12, 2019

Assist. Prof. Dr. Cem Çağrı DÖNMEZ

Abdulkadir Atalan

Abbreviations

AN	Advanced Nurse
ANOVA	Analysis of Variance
C	Clerks for Check in and Check out
DOE	Design of Experiment
CCD	Central Composite Design
EVOP	Evolutionary Operations
FIFO	First-in First-out
GDP	Gross Domestic Product
GDP PC	Gross Domestic Product Per Capita
GHCI	Global Healthcare Competitiveness Index
E	Health and Social Employment
ER	Exam Room
ES	Emergency Services
HCI	Healthcare Competitiveness Index
HE	Healthcare Expenditure
HE PC	Healthcare Expenditure Per Capita
HMO	Healthcare Maintenance Organization
IPHSF	Private Healthcare Systems in Interactive Case for Funders
IPHSP	Private Healthcare Systems in Interactive Case for Provider
ISHSF	State Healthcare Systems in Interactive Case for Funders
ISHSP	State Healthcare Systems in Interactive Case for Provider
LE	Life Expectancy
LOS	Length of Stay
Max	Maximum or Maximize
Max Rev _p	Maximization of Private Healthcare Provider and Funder Revenue
Max Rev _s	Maximization of Public Healthcare Funder Revenue
MD	Medical Doctor
Min	Minimum or Minimize
MOM	Multi-Objective Optimization Model
MPHSF	Private Healthcare Systems in Monopoly Case for Funders
MPHSP	Private Healthcare Systems in Monopoly Case for Provider

MS	The Mean Sum of Squares
MSHSF	State Healthcare Systems in Monopoly Case for Funders
MSHSP	State Healthcare Systems in Monopoly Case for Provider
NN	Normal Nurse
OECD	Organization for Economic Co-operation and Development
PE	Pharmaceutical Expenditure
PPO	Preferred Provider Organization
PO	Treated Patients Output
RSM	Response Surface Analysis
SCHIP	The State Children's Health Insurance Program
SS	The Sum of Squares
TR	Triage Area
TRICARE	A health insurance plan providing coverage to current and retired members of the U.S. armed forces
UCI	Urban Competitiveness Index
WHO	World Health Organization
WT	Waiting Time

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Chapter 1: Evaluation of Monopoly and Interactive Relationships Between the Public and Private Healthcare Systems to Establish Optimization Models

1.1. Introduction to Healthcare Systems

Healthcare structures have dynamic settings, multifaceted, and become large (Cabrera, Taboada, Iglesias, Epelde, & Luque, 2011). Extraordinary costs, limited budget, and inadequate healthcare resources cause challenges in busy healthcare organizations (Ahmed & Alkhamis, 2009). Healthcare systems have mainly two objectives, which are cost and health services in order to provide profit. Spending less and high patient satisfaction are desired by health systems. Generally, the levels of spending are measured by the satisfaction of patients (E. S. Fisher et al., 2003), and (Dansky & Miles, 1997). Vulgarly, there are four main players in health system that are patients, healthcare providers, funders, and the policy/rule maker government. And all of these parts have different objectives.

Patients can, in some cases, lessen their out-of-pocket insurance and healthcare costs by limiting their utilization of provider services and/or by purchasing less insurance (Alexander, Casalino, & Meltzer, 2003). Patients try to have three objective functions which are having quality care, minimizing health expenses cost (F. et al., 1993), and easy to access to health service or delivery (Kenagy, Berwick, & Shore, 1999).

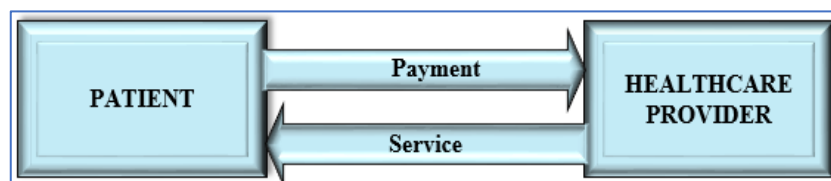


Figure 1: The Simple Payment Process

Providers such as physicians, nurses, physicians' assistants, registered nurses, administrators, etc. set their prices for patient services to maximize their profits; prices are determined by the procedure and diagnosis codes established by the insurance companies, which are pre-negotiated between providers and insurers (Xavier, 2003). Increasing patient satisfaction, high quality service, gaining experience, and maximizing profits are health

provider's goals. In the U.S., patients who has PPO (Preferred Provider Organization) are more flexible to choose providers, while patients who have an HMO (Health Maintenance Organizations) plan can only receive health service from a healthcare provider within the HMO system (Kogan, Leu, & Chernonog, 2014).

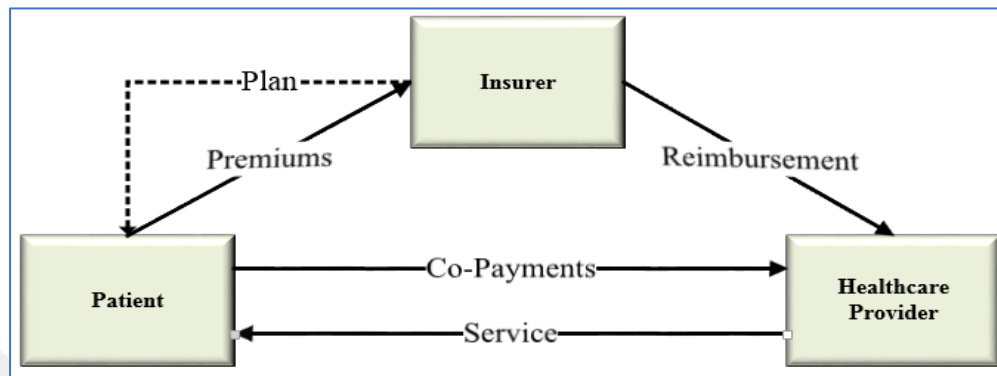


Figure 2: The Third-Party Payer Process

Private insurance companies and public funders strive to minimize costs by limiting payments to providers and/or by raising patient (or employer) premiums or implementing copayment systems. The private insurance companies aim to increase the number of customers and want to prolong the insurance premiums along with public funders such as government wants to minimize patient's reimbursement and the waiting time. In some countries where have social health system, as the UK, etc., the waiting times is longer than in the other countries as the US, Europe (Siciliani, Stanciole, & Jacobs, 2009).

Patients wait for non-emergency treatment almost three months in some countries, even can extend into years (Brekke, Siciliani, & Straume, 2008). Waiting time is one of the major problem in public health system (Trzeciak & Rivers, 2003). Many of studies show that the waiting time has the cost-impact of the funders and providers. Siciliani, Stanciole, and Jacobs (2009) research the resistance of hospital costs with respect to waiting times. They find that hospital costs and waiting time has a U-shape correlation, because the waiting time on cost is nonlinear (Siciliani et al., 2009). These kinds of studies care in long term treatment; however, we consider daily waiting time in hospitals and it effects the waiting time cumulatively (Fetter & Thompson, 1996). Under this circumstance, we try to find solution using interaction between healthcare components that gives patients an opportunity to elect treatment among providers.

A Hoteling model with two districts that diverge in technology to research the influence

of patient mobility on health care quality, health care funding and welfare are studied by researches (Brekke, Levaggi, Siciliani, & Straume, 2014). Patient mobility that means patient becomes able to choose providers and elective treatments in the EU has been studied by some researches. Cross-border healthcare guidelines using game theory approach in optimization models were developed by Andritsos and Tang in 2014 for Europe healthcare systems. They suggested that cross-border methodology yields low cost to patients and funders, and high health service utility. In addition, this provides flexibility in selecting hospitals which have helpful for patients (Danis, Biddle, & Goold, 2002). They examine cross-border healthcare policy (to choose the country patient receives a treatment) to increase patient mobility in order to minimize the waiting time in public hospitals and funder's cost. Some of these studies care distance between providers and some not. General overview, patients have free travelling to receive treatment among European Countries (Sunol, P, & A., 2008). In our research, patients who have private or public insurance can choose any providers in the same districts. Therefore, the distance between providers is minor detail and insignificant in our approach.

Generally, using simulation approach, along with optimization technique that depends on cost/benefit optimization is developed by researches in order to solve the healthcare systems problems (Ahmed & Alkhamis, 2009; Barton, 2001; Batun & Begen, 2013; Cabrera et al., 2011; Feili, 2013; Kelton & Barton, 2003; Montevechi, Pinho, & Leal, 2007; Vohra, 2012). Many of these studies have locally solved these kinds of problems such as improving clinic capacity (Cochran & Roche, 2009), reducing waiting time in emergency department (Ajami, Ketabi, & Mahmood Abadi, 2013), re-scheduling (Beaulieu, Ferland, Gendron, & Michelon, 2000), etc. to improve patient satisfaction. Optimization approach for health system is inevitable, otherwise, it is difficult to solve problems analytically and statistical in order to try to minimize waste and maximize efficiency. In this research, all developed models are utilized using the mechanism design approach. The healthcare system has a complex structure, and mechanism design helps to cope with this system. Recently, Kogan (2014) and Andritsos (2013) used this concept in healthcare systems to provide the best outcome among design strategies. In mechanism design, agents who will consume the resources detain optimizing the sharing of properties (Vohra, 2012).

The main reason for this research is to increase the quality of the patient both in public healthcare institutions and private healthcare institutions. Looking at the world, there are two types of problems that belong to these organizations. First, patients stay longer in public

hospitals, so patient dissatisfaction and state costs are increasing. The second problem belongs to private healthcare institutions. In this problem, the waiting time of the patients is low, and the cost is high. This means that patients need to pay a lot from their pocket to wait less. For this reason, the number of patients treated annually in private healthcare institutions is decreasing.

There are two structures in the world healthcare system which are the public healthcare system and the private healthcare system. There are many components that built up these healthcare systems. Especially, patients, government (as the main rule/policy maker), healthcare providers, and private healthcare entrepreneurs (private insurance companies, hospitals, providers) are centered in the healthcare system. Generally, the impacts of healthcare systems competition on quality are examined to analyze by researchers. Instead of this approach, structural and financial cooperation among healthcare components should be examined to reduce problems and provide delivering good patient care and service.

This chapter is designed as follows: the methodology of the research is explained in Section 2. The monopoly healthcare system and collaboration among the healthcare system components are placed and heuristic models of these parts are constructed in this section. Numeric examples are provided in Section 3. Conclusively, Section 4 includes conclusions and discussions of this research.

1.2. Types of Healthcare Systems

There are two types of healthcare systems in the world. These are public and private healthcare systems (Figure 3). The management of these systems may differ in terms of countries (Zerda, Velásquez, Tobar, & Vargas, 2002). In addition, the governance structure of countries may also differ in their healthcare systems. In addition, the governance structure of countries may also differ in their healthcare systems.

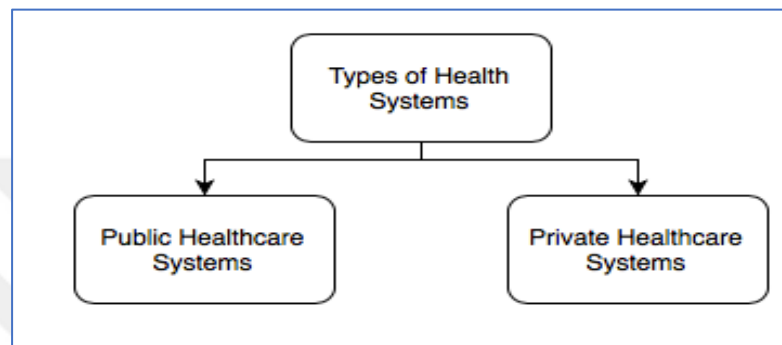


Figure 3: The Types of Healthcare Systems

National governments play a major role in healthcare systems. For this reason, the influence of the governments of the countries on the structure of the healthcare systems is very high. While not being an ideal healthcare system, there are some suggestions for an ideal healthcare system. For example; Social assistance, Social insurance, Social security, Private insurance models (Zerda et al., 2002). Another healthcare system that is proposed includes four models which are The Beveridge Model, The Bismarck Model, The National Health Insurance Model, The Out-of-Pocket Model (Wallace, 2013).

While considering these healthcare systems, it is necessary to examine healthcare insurance companies together. Healthcare systems are also mentioned in the introduction section, healthcare insurance companies are placed among the components of the healthcare systems. Similar to healthcare systems, there are private and public healthcare insurance institutions. In public healthcare insurance companies, the government determines the premium rates without regard to the treatment of patients or those who own this healthcare insurance. According to some special circumstances, the public insures people with low income (Medicaid in USA, Green card in Turkey, etc.) and those who are old (Medicare in USA), free of charge. However, the system applied by private insurance companies is slightly different. The coverage

of the insurance you own may vary depending on the type of treatment. This means that people with this type of insurance may have to pay extra money.

1.2.1. Public Healthcare System

States or governments play a leading role in the state or public healthcare system. It gives direction to the healthcare system through the legal regulations of the states. These legal regulations adversely affect the healthcare system, sometimes on a positive basis. In some countries public -based healthcare systems are failing. This increases the cost of healthcare expenditure. This adverse situation, which is reflected in the illness, obliges patients to lead to private healthcare institutions or to travel to other countries to be treated. From this point of view, both the state does not benefit, and the patients spend more money to be treated. With this implementation, optimization models have been developed to prevent any side from harming both the government and the patient.

1.2.2. Private Healthcare System

Organizations belonging to the private healthcare system have emerged because the public healthcare system is inadequate. In countries with social and non-social structures, the development of the private healthcare system is changing. States in the social structure are paying a large part of their healthcare care expenditures. However, private healthcare systems have developed since non-social states have received limited healthcare expenditure. In addition, the healthcare sector in countries such as the U.S., japan is the largest after production.

In this structure, the governments are defined as the main rule and law makers. It operates according to the legal framework established by the private healthcare institutions. In this system, patients with public healthcare insurance cannot be treated at large, or patients can be treated by paying a certain fee. It causes fewer patients to benefit from private healthcare facilities. With this study, it is ensured that patients with public healthcare insurance are treated in private healthcare enterprises by setting some scenarios. Thus, the most important problem in the public healthcare system will be reduced patient waiting time, as well as the number of patients treated in the private healthcare system will increase and the annual incomes will increase. All parties involved in the private healthcare system will benefit.

1.3. Methodology

In the first part of this thesis, in the first two chapters, relevant literature research and information about healthcare systems are given. In order to understand the method developed for research belonging to this division, the determined system needs to be known and recognized. This system is shown in the following diagram (see Figure 4) At the same time, it has been systematically modeled as it is on this schematic so that the developed optimization models can be understood.

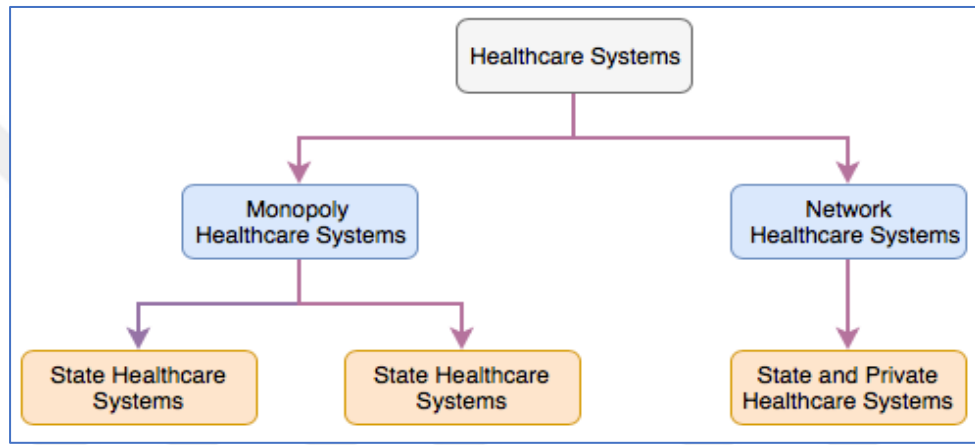


Figure 4: Healthcare Systems and Sub-units

The problem formulation of this research is combined in two segments. The first part consists of the single healthcare provider, funders and elective treatment as monopoly. Interactions between healthcare components are studied in the second section. In this part, each healthcare organ can take an advantage among them. In the third section, we considered funders profits using heuristics methods in pervious sections.

▪ Notations

Contemplating two types of parameters among the healthcare components with index $i = s, p$ all notations are presented in Table 1. This index is situated as private and public healthcare constituents. The patient population is measured from N to 1 (Andritsos & Tang, 2014).

Table 1: Notations

Sets	Definitions
$i = \{s, p\}$	Contemplating parameters among the state/public and private healthcare components
Parameters	Definitions
α_i	The coefficient associated with the waiting time i
β	Charge by private funders
Decision Variables	Definitions
k_i	The unit cost for treating patient type i
c_i	Co-payment by the patient i who visit to the doctor each time
r_i	Reimbursement rate by insurance i
p_i	Payment to be insured by patient i
w_i	Waiting time i
λ_i	Arrival rate of patient i
μ_i	Processing rate of patient i
x_i	Proportion of population with insurance i

▪ Queuing Systems in Healthcare Area

Literature research shows that cost of queuing theory is inversely proportional to a certain level. Likewise, high waiting time is also known to cause high costs in hospital establishments (Gorunescu, McClean, & Millard, 2002). By considering the funder's reimbursement cost is related with the waiting time that is called disutility and formulated as $r(\alpha)w$, where r is reimbursement, α is the disutility coefficient associated with waiting w (Andritsos & Tang, 2014). In this research, the relationship between patient satisfaction and waiting time is measured by the premium paid to obtain the health care service. This shows that; Higher paying premiums lead to shorter waiting times.

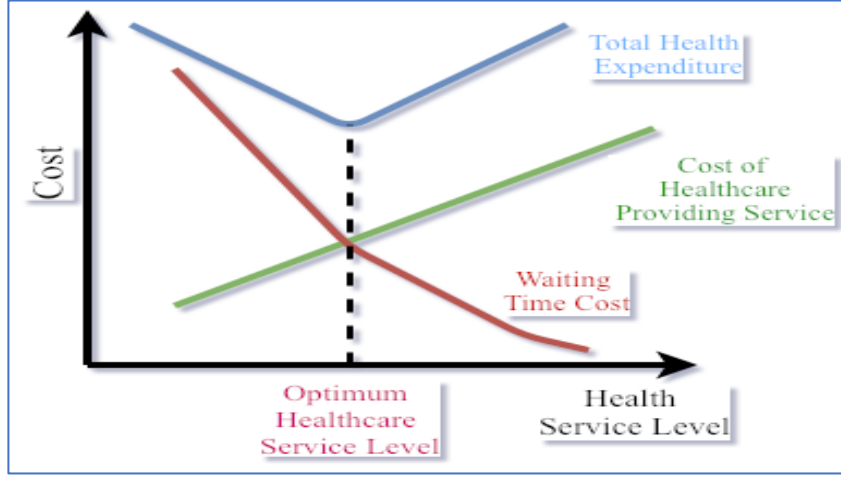


Figure 5: Decision Variables Input Parameters

Healthcare institutions that obtain this patient satisfaction are usually private institutions. It is observed that there is more waiting time in the public hospitals. These situations cause fewer patients to be treated in the private sector and the annual income is lower. From a different point of view, this is the result of a high waiting time in public hospitals, which increases the cost. At this point, an optimal solution has been found in this research by providing a balance between public -owned hospitals and private institutions.

The patients' satisfaction constraint is measured:

$$p_s \leq \alpha w_s \quad (1)$$

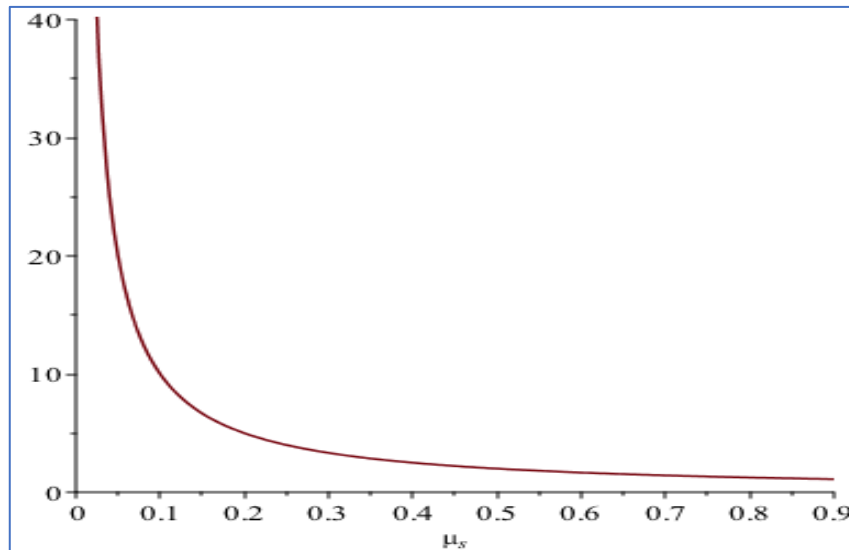


Figure 6: Exponentially distributed with mean $1/\mu$

Where w is indicated as the waiting time for treatment. Treatment processing time is exponentially distributed with mean $\frac{1}{\mu}$ (see Figure 6 and Figure 7) and $M/M/1$ queuing model is applied to calculate that the expected waiting time of a patient at the provider's places is:

$$w = \frac{1}{\mu - \lambda} \quad (2)$$

The queuing theory behaves the patient arrivals are Poisson distributed with rate λ whereas treatment times are exponentially distributed with rate μ . The ratio λ/μ is called utilization ρ . If this ratio is greater than 1, that says patients are arriving faster than they can be served, and so the waiting time will grow without bound. If the ratio is less than 1, the waiting time will reach some steady state averagely. In this study, the healthcare service time is not fixed, so the curve does trend down rapidly when μ exceeds 1 and λ falls in behind 1.

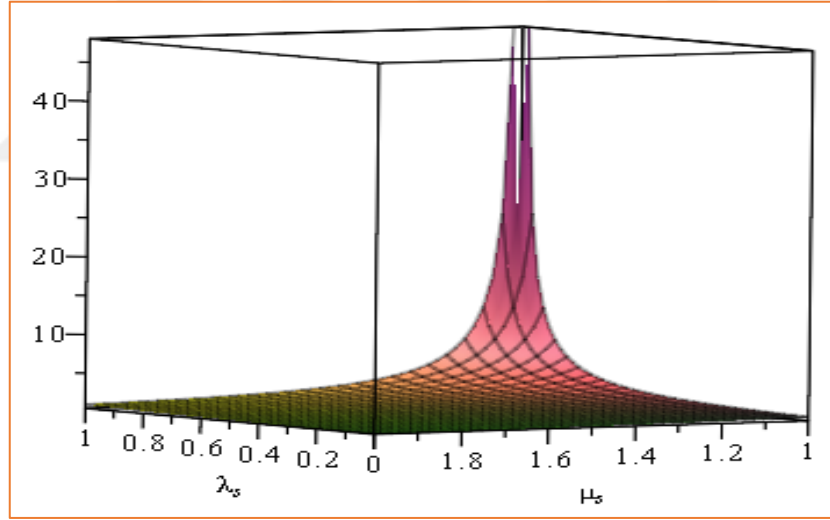


Figure 7: The relationship between λ and μ

In this study, arrival rate and processing rate are defined as the number of patients per time. To calculate the expected waiting time in queue W_q that is needed to estimate the expected number of patients L_s , the expected waiting time in the healthcare system and the effective arrival rate at the system λ_{eff} along with λ_{lost} . As mentioned parameters are known as a little's formula (Hamdy, 2010).

$$\lambda_{eff} = \lambda - \lambda_{lost} \quad (3)$$

where λ_{lost} means that some of arrivals do not join because the system is full. However, arrival

all patients are treated by the system. Hence, $\lambda_{lost} = 0$.

Arrival rates is assumed as: $\lambda_{eff} = \lambda$. The expected number of customers are calculated as:

$$L_s = \sum_{i=1}^{\infty} x P_x \quad (4)$$

And;

$$\sum_{i=1}^{\infty} x P_x = x_0 P_0 + x_1 P_1 + x_2 P_2 + \dots + x_n P_n = 1 \quad (5)$$

$$L_s = 1 \quad (6)$$

Where $x = 1$, and $P_x = 1$.

The waiting time in the system is estimated;

$$W_s = \frac{L_s}{\lambda} \quad (7)$$

We consider the waiting time in the queue that is formulated as;

$$W_q = \left(\frac{L_s}{\lambda} \right) - \left(\frac{1}{\mu} \right) \quad (8)$$

$$W_q = \left(\frac{\sum_{i=1}^{\infty} x P_x}{\lambda} \right) - \frac{1}{\mu} \quad (9)$$

So that;

$$W_q = \left(\frac{1}{\lambda} \right) - \left(\frac{1}{\mu} \right) \quad (10)$$

And;

$$W_q = \frac{\lambda - \mu}{\lambda \mu} \quad (11)$$

As a result, according to the M/M/1 rule, the total waiting time of a patient in both the system and the queue is calculated as follows;

$$W_{total} = \frac{\lambda + \mu}{\mu * (\mu - \lambda)} \quad (12)$$

1.3.1. Monopoly System between Healthcare Components

This system has two parts that cooperate only patients and funders as if a patient has a public insurance, he/she can just get service from the public providers, and vice versa. Therefore, the system behaves as a monopoly.

There are two main incidents for patients who seek treatment in private or public healthcare services. If patients are eligible to have public insurance such as Medicaid, Medicare, SCHIP, Tricare, etc., the resources of the state or government cover all of the patient's expenses. This situation causes high reimbursement cost for government and high waiting time in public hospitals (Jha, Orav, & Epstein, 2011). The second portion is that the patient has private insurance. In this condition, the patient has to pay more to have insurance in order to receive good service from healthcare care providers. Our optimization models were used to target and achieve these problems subject to constraints.

The first model includes public providers and public funders. The models goal function for the public hospital's profit is nonnegative (Andritsos & Tang, 2014). The second model consists of private providers and private insurance. The objective function of this formulation is to maximize total revenue subject to the hospital reimbursement rate r , co-payment by the patient i who visit to the doctor each time c , and the unit cost for treating a patient k presented as the unit cost of hospital capacity that includes the cost of providers, materials, admissions, etc.

1.3.1.1. Public Healthcare System

Two objective functions have been considered in the optimization model developed for public hospitals. In the first model, the treatment cost of the patients treated in the hospital is set to minimum and in the second model, the waiting time of the patients is set at minimum level.

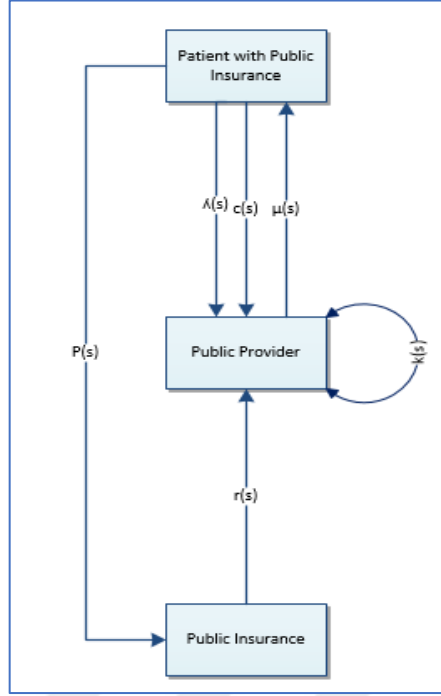


Figure 8: Public Healthcare in Monopoly System

The patient who has public insurance receives service from public providers as exhibited in Figure 8. The patients' public insurance does not cover the cost of healthcare service from the private providers. Thereby the public hospitals have to incur a high volume of patients, which leads to an increase in waiting time. All of these negations result in unsatisfied patients and a high cost to the government.

Same as private healthcare systems, the rate of patients only treatment, received treatment, and total customers formulated as;

$$\mu_s < \lambda_s < x_s < 1 \quad (13)$$

Using the same denoted parameters as case 1; the public hospitals expected profit must be nonnegative and is computed since $\lambda_s(r_s + c_s) \geq \mu_s k_s = 0$ (Andritsos & Tang, 2014). The constraint of the hospitals reimbursement and the unit cost for treating a patient are formulated as:

$$\lambda_s(r_s + c_s) \geq \mu_s k_s \quad (14)$$

Where the proportion of private insured patients with multiply the insurances, premiums must be:

$$x_s p_s - \lambda_s r_s \geq 0 \quad (15)$$

Reducing the total of expenses for all persons is to aim of the government (Hoel & Saether, 2003). By contemplating the patients waiting time who are treated in public providers can be invented as:

$$Waiting\ time_s = \min \sum \frac{\lambda + \mu}{\mu(\mu - \lambda)} \quad (16)$$

Subject to 1, 13, 14 and 15.

▪ **Mathematical expansion of objective function equation and constraints for public healthcare sector:**

- Mathematical expansion of the objective function of the public healthcare system:

- Expended 0:

$$Waiting\ time_s = \min \left[\frac{\lambda + \mu}{\mu(\mu - \lambda)} \right]$$

- Expended 1:

$$Waiting\ time_s = \left\lceil \frac{\mu_s}{\mu_s(\mu_s + \lambda_s)} \right\rceil + \left\lceil \frac{\lambda_s}{\mu_s(\mu_s + \lambda_s)} \right\rceil$$

- * The cost of a patient's treatment seems to be related to the time required for the treatment:

$$\lambda_s(r_s + c_s) \geq \mu_s k_s$$

$$\left\{ \begin{array}{l} \left\lceil \left[\frac{[\lambda_s(r_s + c_s)]}{k_s} \right] \right\rceil \leq \mu_s : 0 > k_s \\ [\mu_s = \mu_s] : k_s = 0 \\ \left\lceil \left[\frac{[\mu_s \leq \lambda_s(r_s + c_s)]}{k_s} \right] \right\rceil : 0 < k_s \end{array} \right.$$

- * The hospitals reimbursement is related to the rate of hospital admission as below:

$$x_S p_S - \lambda_S r_S \geq 0$$

$$\begin{cases} \left[\left[\frac{[\lambda_S \leq (p_S x_S)]}{r_S} \right] \right]: & 0 < r_S \\ [\lambda_S = \lambda_S]: r_S = 0 \text{ and } 0 \geq p_S x_S \\ \left[\left[\frac{[\lambda_S \geq (p_S x_S)]}{r_S} \right] \right]: & r_S < 0 \\ []: & \text{otherwise} \end{cases}$$

1.3.1.2. Private Healthcare System

The patient who has private insurance obtains service from private providers. Although public healthcare services cost less, the patients who have private insurance are not eligible to receive healthcare service from public providers. Hence the private providers operate in a low volume or capacity as displayed in Figure 9.

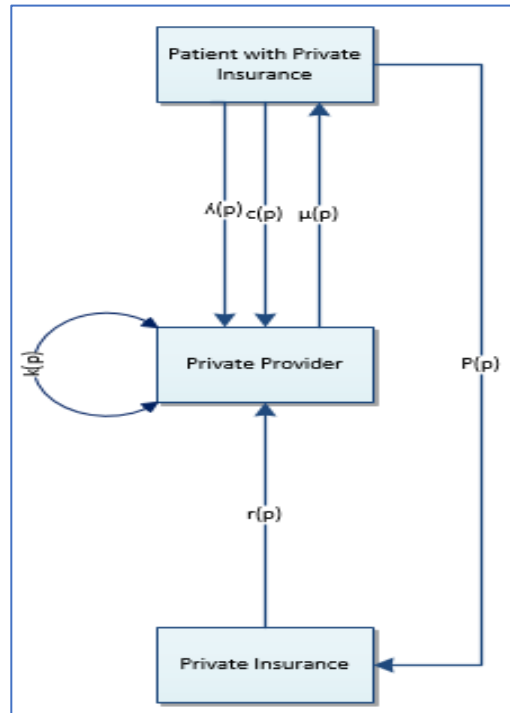


Figure 9: Private Healthcare in Monopoly System

Patients try to pursue treatment from private providers which have lesser waiting time (Andritsos & Tang, 2014). The private provider has the patient arrival rate λ and processing rate μ . The hospitals expected profit is $\lambda_p(r_p + c_p) - \mu_p k_p$. The constraint of the hospitals reimbursement and the unit cost for treating a patient is formulated as;

$$\lambda_p(r_p + c_p) \geq \mu_p k_p \quad (17)$$

The private providers expected profit must be positive so by considering the unit cost for treating a patient and the hospital's reimbursement are established as;

$$\lambda_p r_p \geq \mu_p k_p \quad (18)$$

The number of customers x_i who are insured by funders do not count the total number of patients in all area where necessitate an insurance. Since patients only seek care is;

$$\lambda_p < \mu_p < x_p < 1 \quad (19)$$

Where the proportion of private insured patients with multiply the insurances premiums must be;

$$x_p p_p \geq \lambda_p r_p \quad (20)$$

Otherwise, the private hospitals profits become negative. The variation of waiting time is correlated to income differences, as having a higher income that is a higher willingness to pay will escape waiting in hospitals (Hoel & Saether, 2003). Therefore, we assume that the waiting time in private healthcare sector is close to zero. The patient's satisfaction constraint is measured:

$$p_p \geq \alpha w_p = 0 \quad (21)$$

There are two more constraints. The values of the decision variables that make up these constraints vary depending on each other. Must be at most or at least equal to each other.

$$c_p \leq k_p \quad (22)$$

and,

$$p_p \leq r_p \quad (23)$$

Where w is symbolized as the waiting time for treatment. By deliberating the private providers or hospitals profit can be formulated as:

$$MaxRev_p = \sum \lambda_p (r_p + c_p) - \mu_p k_p \quad (24)$$

Subject to 17, 18, 19, 20, and 21.

- ***Mathematical expansion of objective function equation for private healthcare sector:***

When the mathematical expansion of the objective function equations is made, it turns out that there is no linear equation (see *expanded*). In this case, optimization model for monopoly private provider is a non-linear problem.

- Expanded 0:

$$Max Rev_p = \sum \lambda_p (r_p + c_p) - \mu_p k_p$$

- Expanded 1:

$$Max Rev_p = \left(\frac{1}{2}\right) r_p \lambda_p^2 - \left(\frac{1}{2}\right) r_p \lambda_p + \left(\frac{1}{2}\right) \lambda^2 - \left(\frac{1}{2}\right) c_p \lambda_p - \mu_p k_p \lambda_p$$

- Expanded 2:

$$\begin{aligned}
Max Rev_p = & \left(\frac{1}{2}\right) r_p \lambda^2 p - \frac{\left(\frac{1}{4}\right) \lambda p r_p^2}{\left(\frac{1}{2}\right) r_p + \left(\frac{1}{2}\right) c_p} - \frac{\left(\frac{1}{2}\right) r_p \lambda p c_p}{\left(\frac{1}{2}\right) r_p + \left(\frac{1}{2}\right) c_p} \\
& - \frac{\left(\frac{1}{2}\right) r_p \lambda p \mu_p k_p}{\left(\frac{1}{2}\right) r_p + \left(\frac{1}{2}\right) c_p} + \frac{\left(\frac{1}{32}\right) r_p^3}{\left(\left(\frac{1}{2}\right) r_p + \left(\frac{1}{2}\right) c_p\right)^2} \\
& + \frac{\left(\frac{3}{32}\right) r_p^2 c_p}{\left(\left(\frac{1}{2}\right) r_p + \left(\frac{1}{2}\right) c_p\right)^2} + \frac{\left(\frac{1}{8}\right) r_p^2 \mu_p k_p}{\left(\left(\frac{1}{2}\right) r_p + \left(\frac{1}{2}\right) c_p\right)^2} \\
& + \frac{\left(\frac{3}{32}\right) r_p c_p^2}{\left(\left(\frac{1}{2}\right) r_p + \left(\frac{1}{2}\right) c_p\right)^2} + \frac{\left(\frac{1}{4}\right) r_p c_p \mu_p k_p}{\left(\left(\frac{1}{2}\right) r_p + \left(\frac{1}{2}\right) c_p\right)^2} \\
& + \frac{\left(\frac{1}{8}\right) r_p \mu_p^2 k_p^2}{\left(\left(\frac{1}{2}\right) r_p + \left(\frac{1}{2}\right) c_p\right)^2} + \left(\frac{1}{2}\right) c_p \lambda^2 p - \frac{\left(\frac{1}{4}\right) \lambda p c_p^2}{\left(\frac{1}{2}\right) r_p + \left(\frac{1}{2}\right) c_p} \\
& - \frac{\left(\frac{1}{2}\right) c_p \lambda p \mu_p k_p}{\left(\frac{1}{2}\right) r_p + \left(\frac{1}{2}\right) c_p} \\
& + \frac{\left(\frac{1}{32}\right) c_p^3}{\left(\left(\frac{1}{2}\right) r_p + \left(\frac{1}{2}\right) c_p\right)^2} + \frac{\left(\frac{1}{8}\right) c_p^2 \mu_p k_p}{\left(\left(\frac{1}{2}\right) r_p + \left(\frac{1}{2}\right) c_p\right)^2} \\
& + \frac{\left(\frac{1}{8}\right) c_p \mu_p^2 k_p^2}{\left(\left(\frac{1}{2}\right) r_p + \left(\frac{1}{2}\right) c_p\right)^2} - \frac{\left(\frac{1}{16}\right) r_p^2}{\left(\frac{1}{2}\right) r_p + \left(\frac{1}{2}\right) c_p} - \\
& - \frac{\left(\frac{1}{8}\right) r_p c_p}{\left(\frac{1}{2}\right) r_p + \left(\frac{1}{2}\right) c_p} - \frac{\left(\frac{1}{4}\right) r_p \mu_p k_p}{\left(\frac{1}{2}\right) r_p + \left(\frac{1}{2}\right) c_p} \\
& - \frac{\left(\frac{1}{16}\right) c_p^2}{\left(\frac{1}{2}\right) r_p + \left(\frac{1}{2}\right) c_p} - \frac{\left(\frac{1}{4}\right) c_p \mu_p k_p}{\left(\frac{1}{2}\right) r_p + \left(\frac{1}{2}\right) c_p}
\end{aligned}$$

$$-\frac{\left(\frac{1}{4}\right)\mu_p^2 k_p^2}{\left(\frac{1}{2}\right)r_p + \left(\frac{1}{2}\right)c_p}$$

- The most important factor in increasing annual incomes in private health care is the number of patients treated in one year. For this reason, private health care will want to increase the number of patients. This is called maximization of the objective function without increasing patient waiting time. In simple terms, the rate of patient arrival is calculated as follows:

$$\lambda_p = \left[\frac{[2k_p\mu_p + c_p + r_p]}{r_p} + c_p \right]$$

- The treatment time required for the patient to be treated:

$$\mu_p = \frac{1}{2 \left[\frac{c_p\lambda_p + r_p\lambda_p - c_p - r_p}{k_p} \right]}$$

- *Decision variables (λ_p and μ_p) expansion of objective function equation for private health sector:*

- **Considering the first constraint:** The constraint of the hospitals reimbursement and the unit cost for treating a patient is formulated as;

- * Looking at mathematical formulas in the first constraint, the hospitals reimbursement is related to the rate of hospital admission as below;

$$\begin{cases} [r_p = r_p]: \lambda_p = 0 \text{ and } -\mu_p k_p \geq 0 \\ \left[-\left[\frac{c_p\lambda_p - k_p\mu_p}{\lambda_p} \right] \leq r_p \right]: 0 < \lambda_p \\ \left[r_p \leq -\left[\frac{c_p\lambda_p - k_p\mu_p}{\lambda_p} \right] \right]: 0 > \lambda_p \\ []: \text{otherwise} \end{cases}$$

- * The cost of a patient's treatment seems to be related to the time required for

the treatment;

$$\left\{ \begin{array}{l} [k_p = k_p]: \mu_p = 0 \text{ and } 0 \leq \lambda_p(r_p + c_p) \\ \left[k_p \leq \left\lceil \frac{[\lambda_p(r_p + c_p)]}{\mu_p} \right\rceil \right]: 0 < \mu_p \\ \left[\left\lceil \frac{[\lambda_p(r_p + c_p)]}{\mu_p} \right\rceil \leq k_p \right]: 0 > \mu_p \\ []: \text{otherwise} \end{array} \right.$$

- **Considering the second constraint:** The private providers expected profit must be positive so by considering the unit cost for treating a patient and the hospitals reimbursement are established. The second constraint equation shows how the time required for the treatment of the patient is related to the cost of the treatment.

$$\left\{ \begin{array}{l} \left[\left\lceil \frac{[\lambda_p r_p]}{k_p} \right\rceil \leq \mu_p \right]: k_p < 0 \\ [\mu_p = \mu_p]: k_p = 0 \\ \left[\mu_p \geq \frac{[(\lambda_p r_p)]}{k_p} \right]: 0 < k_p \end{array} \right.$$

- **Considering the third constraint:** The number of customers who are insured by funders do not count the total number of patients in all area where necessitate an insurance. The relationship between the number of patients with health insurance and the monthly premium paid for health insurance appears in the third constraint equation. This constraint needs to be examined in terms of both premiums and health insurance holders.

* The number of customers who are insured by funders:

$$\left\{ \begin{array}{l} [x_p = x_p]: p_p = 0 \text{ and } \lambda_p r_p \leq 0 \\ \left[\left\lceil \frac{[\lambda_p r_p]}{p_p} \right\rceil \leq x_p \right]: 0 < p_p \\ \left[\left\lceil \frac{[\lambda_p r_p]}{p_p} \right\rceil \leq x_p \right]: p_p < 0 \\ []: \text{otherwise} \end{array} \right.$$

* Premium for healthcare insurance:

$$\left\{ \begin{array}{l} [p_p = p_p]: x_p = 0 \text{ and } \lambda_{prp} \leq 0 \\ \left[\left[\frac{[\lambda_{prp}]}{x_p} \right] \leq p_p \right]: 0 < x_p \\ \left[\left[\frac{[\lambda_{prp}]}{x_p} \right] \leq p_p \right]: x_p < 0 \\ []: \text{otherwise} \end{array} \right.$$

1.3.1.3. Public Healthcare Funders

Patients insured by the state in the public healthcare system have a very long treatment period. This waiting time is reflected in the cost of the state/government budget. People who work in the public sector and those who have low income enjoy the benefit of this type of policy. But even states with a social structure are receiving cheap premiums for their citizens who have this insurance and citizens have the obligation to have this insurance in some states. For this reason, public insurance is required to be registered at least \$50.00 (Barnett & Berchick, 2017) (or 53.00 TL (SGK, 2016)). However, as the amount of premium of healthcare insurance increases, the scope of the insurance coverage expands.

Unfortunately, in some citizens of states are being treated in a limited manner when they cannot pay high premiums. As a matter of fact, this policy of the states' health insurance seems to be wrong. Because the patients who pay a small premium and the patients who pay too much premium are in the same public hospitals, the waiting times are the same and higher. The density of the public hospitals is reduced by the referral to the private healthcare institutions of the patients who have more premiums. As a result, patient waiting time in public hospitals has been reduced and private healthcare sectors' annual income will increase.

The aim of public healthcare insurance is to have the maximum income, but the cost of patients treated in hospitals should not exceed the income. Otherwise, health insurance institutions, the state/government, will be exposed to high costs. The objective function (see equation 25) is constructed as follows:

$$Max Rev_S = \sum_n^N [x_s p_s - \lambda_s r_s] \quad (25)$$

- Mathematical expansion of the objective function of the Public Health Funders:

$$Max Rev_S = \left(\frac{1}{2}\right) p_s \left(x_s + \frac{-\left(\frac{1}{2}\right) p_s - r_s \lambda_s}{p_s} \right)^2 - \frac{\left(\frac{1}{2}\right) \left(-\left(\frac{1}{2}\right) p_s - r_s \lambda_s\right)^2}{p_s}$$

The public healthcare insurance must have only one restriction to avoid lost. The annual income of public insurance should not be less than the cost of the patient being treated within that year (see equation 26).

$$Constraint = \lambda_s r_s + \lambda_s c_s - \mu_s k_s \leq x_s p_s \quad (26)$$

1.3.1.4. Private Healthcare Funders

Private health insurance companies want to save more customers. However, the patients who are the customers are in agreement with the hospitals where they will be treated. Because private health insurance companies want to pay at least the reimbursement they will pay to the hospitals. For private health insurance companies, the objective function is expressed as follows:

$$MaxRev_p = \sum x_p p_p - \lambda_p r_p \quad (27)$$

There are two restrictions on private health insurance. First, the amount of reimbursement to be paid to the hospital must be greater than or equal to the amount of the co-payment and the treatment fee of a patient with private health insurance (see equation 28).

$$Constraint_1 = \lambda_p r_p \geq \lambda_p c_p + \mu_p k_p \quad (28)$$

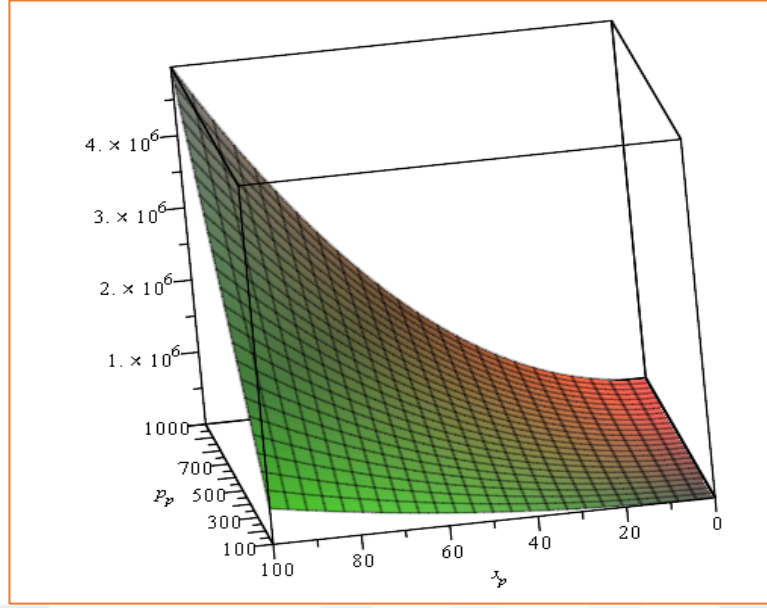


Figure 10: Private Funders' Customers and Premium

The second constraint is that the premium to be paid by the clients with private health insurance should be equal to or greater than the total reimbursement to be paid to the hospital (see equation 29).

$$Constraint2 = \lambda_p r_p \leq x_p p_p \quad (29)$$

The relationship between the number of registered customers for private health insurance and the monthly premium paid by the customer is clearly shown in the Figure 10 below.

1.3.2. Collaborations between Healthcare Components

Two topics are covered under this heading. These are interactions between doctors from both public and private health institutions and health insurance companies. The purpose of this distinction is to have individual purpose-functions and constraints of each health component. But the only component that is affected by all of them is the patient.

1.3.2.1. Networks between Healthcare Providers

In this section, we set up our model in two different scenarios, with each of the health system components networking with each other. The arrival rate λ and discounted reimbursement rate r play the main roles in the problem formulations.

In current health system in most countries, receiving treatment in which hospital depends on type of the patient's insurance. If the patient who has a public insurance, he or she cannot access to receive a treatment in private hospitals or although having a public insurance, the patient must pay for his/her treatment's cost. This constraint cases less patient's mobility to choose hospitals.

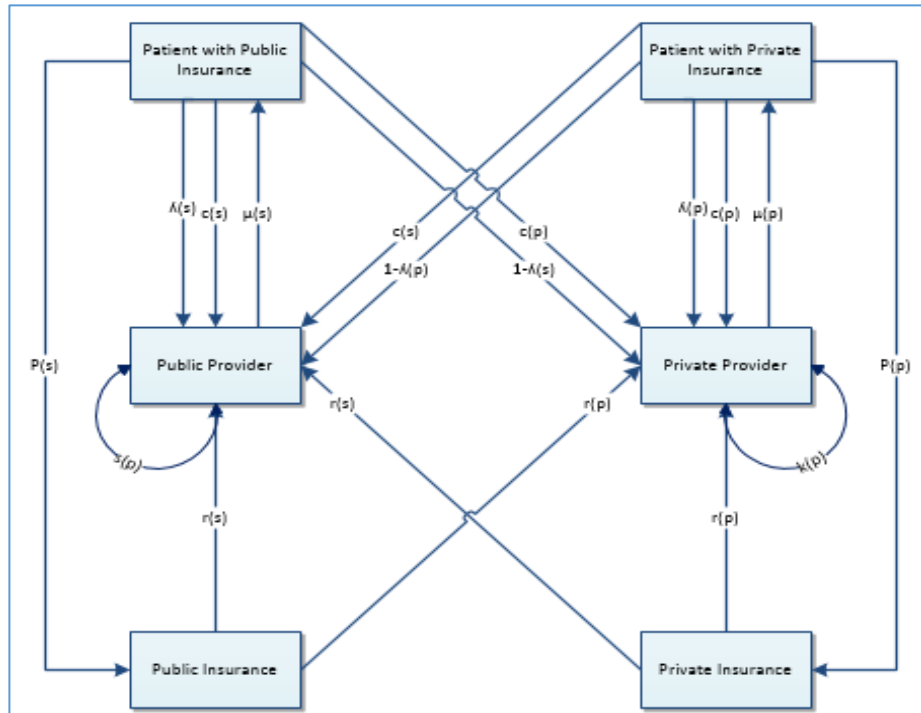


Figure 11: Interaction between Health System Components

The patient who has either private or public insurance obtains service from the private providers with the different or same reimbursement, he/she can access treatment in public or private providers (As seen in Figure 11). However, this approach has some constraints for patients. Fundamentally, minimizing waiting time in public hospitals and increasing the private health sectors expected profits are our goal function in this research.

Private health sector is expected to have no waiting time, which infers that it must have lower capacity utilization. This is associated with the expected revenue of private providers (Hoel & Saether, 2003). The patient who has either private or public insurance obtains service from the private providers with the same reimbursement and the unit cost of hospital capacity.

Patients can be shared between providers, so the arrival and the processing rate constraint which is related to the capacity of private hospitals is:

$$\lambda_p + (1 - \lambda_s) \leq \mu_p + \mu_s \quad (30)$$

Patients can be shared between providers, so the arrival and the processing rate constraint in public hospitals is:

$$\lambda_s + (1 - \lambda_p) \leq \mu_s + \mu_p \quad (31)$$

Otherwise, the waiting time must be unwanted situations and it increases exponentially. Considering the public provider profit should be nonnegative and shown as below:

$$\lambda_s r_s + \lambda_s c_s + (1 - \lambda_p) r_s + (1 - \lambda_p) c_s - \mu_s k_s \geq 0 \quad (32)$$

In this case, where the proportion of private insured patients with multiply the insurances premiums must be zero, because customers who have private insurances have higher payment than public insured customers. Therefore, the public provider's profit is revised as:

$$\lambda_s (r_s + c_s) + (1 - \lambda_p) (r_s + c_s) - (\mu_s + \mu_p) k_s \geq 0 \quad (33)$$

The private providers profit is formulated as:

$$Expected Rev_p = \max \sum \lambda_p(r_p + c_p) + (1 - \lambda_s)(r_s + c_s) - \mu_p k_p - \mu_s k_s \quad (34)$$

The public hospital's waiting time is reformulated as:

$$Waiting\ time_s = \min \left[\frac{\lambda_s}{\mu_s(\mu_s + \lambda_s)} + \frac{1 - \lambda_p}{(1 - \mu_p)((1 - \mu_p) + (1 - \lambda_p))} \right] \quad (35)$$

▪ **Mathematical expansion of objective function equation and constraints for Private health sector:**

* Mathematical expansion of the objective function of the Private health system:

• Expanded 0:

$$Exp Rev_p = \max \sum [\lambda_p(r_p + c_p) + (1 - \lambda_s)(r_s + c_s) - \mu_p k_p - \mu_s k_s]$$

• Expanded 1:

$$Max Rev_p = \lambda_p \lambda_s c_p + \lambda_p \lambda_s r_p + \frac{3}{2\lambda_s r_p} + \frac{3}{2\lambda_s c_p} - k_p \mu_p \lambda_s - k_p \mu_s \lambda_s - \frac{1}{2r_p} \lambda_s^2 - \frac{1}{2c_p} \lambda_s^2$$

• Expanded 2:

$$\begin{aligned} Max Rev_p = & \frac{1}{4} \frac{c_p \lambda_p r_p k_p \mu_s}{\left(-\frac{r_p}{2} - \frac{c_p}{2}\right)^2} + \frac{1}{4} \frac{r_p \lambda_p c_p k_p \mu_p}{\left(-\frac{r_p}{2} - \frac{c_p}{2}\right)^2} + \frac{1}{4} \frac{r_p \lambda_p c_p k_p \mu_s}{\left(-\frac{r_p}{2} - \frac{c_p}{2}\right)^2} \\ & + \frac{1}{4} \frac{r_p \lambda_p r_p k_p \mu_p}{\left(-\frac{r_p}{2} - \frac{c_p}{2}\right)^2} + \frac{1}{4} \frac{r_p \lambda_p r_p k_p \mu_s}{\left(-\frac{r_p}{2} - \frac{c_p}{2}\right)^2} + \frac{1}{4} \frac{c_p \lambda_p c_p k_p \mu_p}{\left(-\frac{r_p}{2} - \frac{c_p}{2}\right)^2} \\ & + \frac{1}{4} \frac{c_p \lambda_p c_p k_p \mu_s}{\left(-\frac{r_p}{2} - \frac{c_p}{2}\right)^2} + \frac{1}{4} \frac{c_p \lambda_p r_p k_p \mu_p}{\left(-\frac{r_p}{2} - \frac{c_p}{2}\right)^2} + \frac{1}{2} \frac{\lambda_p r_p k_p \mu_p}{-\frac{r_p}{2} - \frac{c_p}{2}} \\ & + \frac{1}{2} \frac{\lambda_p r_p k_p \mu_s}{-\frac{r_p}{2} - \frac{c_p}{2}} - \frac{1}{4} \frac{r_p k_p^2 \mu_p \mu_s}{\left(-\frac{r_p}{2} - \frac{c_p}{2}\right)^2} - \frac{1}{2} \frac{c_p \lambda_s \lambda_p c_p}{-\frac{r_p}{2} - \frac{c_p}{2}} \end{aligned}$$

$$\begin{aligned}
& -\frac{1}{2} \frac{c_p \lambda_s \lambda_p r_p}{-\frac{r_p}{2} - \frac{c_p}{2}} + \frac{1}{2} \frac{c_p \lambda_s k_p \mu_p}{-\frac{r_p}{2} - \frac{c_p}{2}} + \frac{1}{2} \frac{c_p \lambda_s k_p \mu_s}{-\frac{r_p}{2} - \frac{c_p}{2}} \\
& -\frac{1}{4} \frac{c_p \lambda_p^2 c_p r_p}{\left(-\frac{r_p}{2} - \frac{c_p}{2}\right)^2} - \frac{1}{4} \frac{c_p k_p^2 \mu_p \mu_s}{\left(-\frac{r_p}{2} - \frac{c_p}{2}\right)^2} + \frac{1}{2} \frac{\lambda_p c_p k_p \mu_p}{-\frac{r_p}{2} - \frac{c_p}{2}} \\
& + \frac{1}{2} \frac{\lambda_p c_p k_p \mu_s}{-\frac{r_p}{2} - \frac{c_p}{2}} - \frac{1}{2} \frac{r_p \lambda_s \lambda_p c_p}{\left(-\frac{r_p}{2} - \frac{c_p}{2}\right)} - \frac{1}{2} \frac{r_p \lambda_s \lambda_p r_p}{\left(-\frac{r_p}{2} - \frac{c_p}{2}\right)} \\
& + \frac{1}{2} \frac{r_p \lambda_s k_p \mu_p}{-\frac{r_p}{2} - \frac{c_p}{2}} + \frac{1}{2} \frac{r_p \lambda_s k_p \mu_s}{-\frac{r_p}{2} - \frac{c_p}{2}} - \frac{1}{4} \frac{r_p \lambda_p^2 c_p r_p}{\left(-\frac{r_p}{2} - \frac{c_p}{2}\right)^2} \\
& - \frac{3}{4} \frac{r_p \lambda_p c_p c_p}{\left(-\frac{r_p}{2} - \frac{c_p}{2}\right)^2} - \frac{3}{4} \frac{r_p \lambda_p r_p c_p}{\left(-\frac{r_p}{2} - \frac{c_p}{2}\right)^2} + \frac{3}{4} \frac{r_p c_p k_p \mu_p}{\left(-\frac{r_p}{2} - \frac{c_p}{2}\right)^2} \\
& + \frac{3}{4} \frac{r_p c_p k_p \mu_s}{\left(-\frac{r_p}{2} - \frac{c_p}{2}\right)^2} - \frac{3}{8} \frac{\lambda_p r_p c_p^2}{\left(-\frac{r_p}{2} - \frac{c_p}{2}\right)^2} + \frac{3}{8} \frac{c_p^2 k_p \mu_p}{\left(-\frac{r_p}{2} - \frac{c_p}{2}\right)^2} \\
& + \frac{3}{8} \frac{c_p^2 k_p \mu_s}{\left(-\frac{r_p}{2} - \frac{c_p}{2}\right)^2} + \frac{3}{4} \frac{r_p k_p \mu_s}{\left(-\frac{r_p}{2} - \frac{c_p}{2}\right)} + \frac{3}{4} \frac{c_p k_p \mu_p}{-\frac{r_p}{2} - \frac{c_p}{2}} \\
& + \frac{3}{4} \frac{c_p k_p \mu_s}{-\frac{r_p}{2} - \frac{c_p}{2}} - \frac{1}{2} \frac{k_p^2 \mu_p \mu_s}{-\frac{r_p}{2} - \frac{c_p}{2}} - \frac{3}{4} \frac{r_p \lambda_p c_p}{-\frac{r_p}{2} - \frac{c_p}{2}} \\
& - \frac{3}{4} \frac{c_p \lambda_p r_p}{-\frac{r_p}{2} - \frac{c_p}{2}} + \frac{3}{4} \frac{r_p k_p \mu_p}{-\frac{r_p}{2} - \frac{c_p}{2}} - \frac{3}{4} \frac{r_p \lambda_p r_p}{-\frac{r_p}{2} - \frac{c_p}{2}} \\
& - \frac{3}{4} \frac{c_p \lambda_p c_p}{-\frac{r_p}{2} - \frac{c_p}{2}} - \frac{1}{2} \frac{\lambda_p^2 c_p r_p}{-\frac{r_p}{2} - \frac{c_p}{2}} - \frac{1}{8} \frac{r_p k_p^2 \mu_s^2}{\left(-\frac{r_p}{2} - \frac{c_p}{2}\right)^2} \\
& - \frac{1}{8} \frac{r_p \lambda_p^2 r_p^2}{\left(-\frac{r_p}{2} - \frac{c_p}{2}\right)^2} - \frac{1}{8} \frac{r_p k_p^2 \mu_p^2}{\left(-\frac{r_p}{2} - \frac{c_p}{2}\right)^2} - \frac{3}{2} \frac{r_p \lambda_s c_p}{-\frac{r_p}{2} - \frac{c_p}{2}}
\end{aligned}$$

$$\begin{aligned}
& -\frac{1}{8} \frac{r_p \lambda_p^2 c_p^2}{\left(-\frac{r_p}{2} - \frac{c_p}{2}\right)^2} - \frac{3}{8} \frac{\lambda_p c_p r_p^2}{\left(-\frac{r_p}{2} - \frac{c_p}{2}\right)^2} - \frac{3}{8} \frac{\lambda_p r_p r_p^2}{\left(-\frac{r_p}{2} - \frac{c_p}{2}\right)^2} \\
& -\frac{1}{2} r_p \lambda_s^2 - \frac{1}{2} c_p \lambda_s^2 - \frac{1}{4} \frac{\lambda_p^2 r_p^2}{-\frac{r_p}{2} - \frac{c_p}{2}} \\
& -\frac{27 r_p c_p^2}{32 \left(-\frac{r_p}{2} - \frac{c_p}{2}\right)^2} - \frac{1}{4} \frac{\lambda_p^2 c_p^2}{-\frac{r_p}{2} - \frac{c_p}{2}} - \frac{1}{4} \frac{k_p^2 \mu_p^2}{-\frac{r_p}{2} - \frac{c_p}{2}} \\
& -\frac{3}{4} \frac{\lambda_s r_p^2}{-\frac{r_p}{2} - \frac{c_p}{2}} - \frac{9 r_p c_p}{-4 r_p - 4 c_p} - \frac{1}{4} \frac{k_p^2 \mu_s^2}{-\frac{r_p}{2} - \frac{c_p}{2}} \\
& -\frac{3}{4} \frac{\lambda_s c_p^2}{-\frac{r_p}{2} - \frac{c_p}{2}} - \frac{27 r_p^2 c_p}{32 \left(-\frac{r_p}{2} - \frac{c_p}{2}\right)^2} - \frac{9 r_p^2}{-8 r_p - 8 c_p} \\
& -\frac{9 c_p^2}{(-8 r_p - 8 c_p)} - \frac{9 r_p^3}{32 \left(-\frac{r_p}{2} - \frac{c_p}{2}\right)^2} - \frac{9 c_p^3}{32 \left(-\frac{r_p}{2} - \frac{c_p}{2}\right)^2}
\end{aligned}$$

* Mathematical expansion of the objective function of the Public Healthcare System:

- Expanded 0:

$$Waitingtime_s = \min \sum \left[\frac{\mu_s + \lambda_s}{\mu_s(\mu_s - \lambda_s)} + \frac{1 - \mu_p + (1 - \lambda_p)}{(1 - \mu_p)(1 - \mu_p - 1 + \lambda_p)} \right]$$

- Expanded 1:

Min Waiting Time_s

$$\begin{aligned}
& = \frac{\mu_s}{\mu_s(\mu_s - \lambda_s)} + \frac{\lambda_s}{\mu_s(\mu_s - \lambda_s)} + \frac{2}{(1 - \mu_p)(-\mu_p + \lambda_p)} \\
& - \frac{\mu_p}{(1 - \mu_p)(-\mu_p + \lambda_p)} - \frac{\lambda_p}{(1 - \mu_p)(-\mu_p + \lambda_p)}
\end{aligned}$$

- Expanded 2:

Min Waiting Time_s

$$\begin{aligned}
&= \mu_p^2 \mu_s + \mu_p^2 \lambda_s - \mu_p \mu_s \lambda_p - \mu_p \lambda_p \lambda_s - \mu_p \mu_s (\mu_s - \lambda_s) \\
&\quad - \lambda_p \mu_s (\mu_s - \lambda_s) - \mu_p \mu_s - \mu_p \lambda_s + \mu_s \lambda_p + \lambda_p \lambda_s + 2\mu_s (\mu_s \\
&\quad - \lambda_s)) / (\mu_s (\mu_s - \lambda_s) \mu_p^2 - \mu_s (\mu_s - \lambda_s) \mu_p \lambda_p - \mu_p \mu_s (\mu_s \\
&\quad - \lambda_s) + \lambda_p \mu_s (\mu_s - \lambda_s)
\end{aligned}$$

1.3.2.2. Networks between Healthcare Funders

The patient can be insured in two ways, either from private insurance companies or public funders. Each of these funders has a different objective function. Private insurance companies want to increase their customers; this is indicated as the x_i proportion of population with insurance. Distinctively, the government or state has to create a budget for the patients who have lower income. Day after day, this population increases in the world. Therefore; the governments try to minimize patients' reimbursement. In order to have optimum outputs, our model is based on sharing patients between providers and funders.

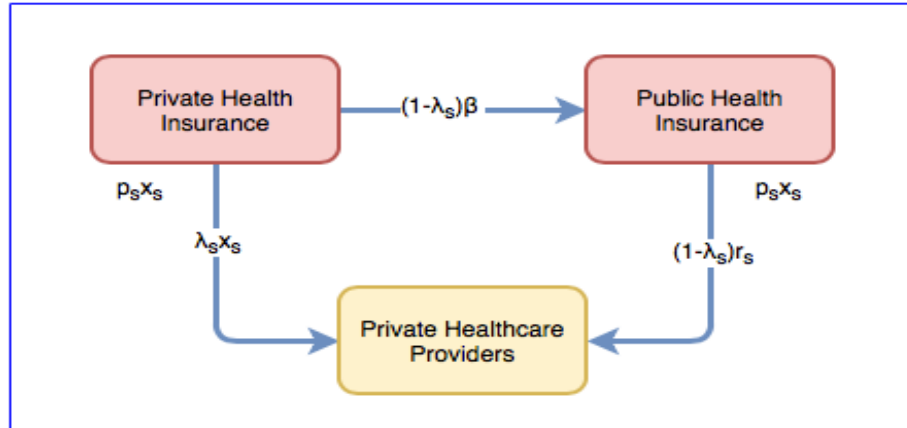


Figure 12: Interaction between Healthcare Funders

The patient who has private or public insurance receive service from either public or private providers. There are two reasons why patients with private health insurance do not choose public hospitals. These are the high premium payments for patients with private health insurance and the high waiting time in public hospitals, which is the reason for dissatisfaction.

However, in this case, waiting time in public hospitals will be reduced as treatment for patients with public healthcare insurance in private hospitals (Figure 12). This will not be an extra cost for the government.

While providing the interaction between health systems, there are five main constraints in terms of insurance institutions. The first constraint is the fact that a patient with a public healthcare insurance is treated in a private hospital and the resulting cost is the interaction between the insurance companies (see equation 36).

$$x_s p_s + (1 - \lambda_s) \beta = (1 - \lambda_s) r_p + r_s \lambda_s + c_s \lambda_s + k_s \mu_s \quad (36)$$

▪ **Mathematical expansion of the β :**

The amount of β appears to be related to the number of patients with public healthcare insurance that are treated in private hospitals (Figure 13).

$$\left\{ \begin{array}{l} [\beta = \beta]: 1 - \lambda_s \text{ and } [\beta = \beta]: 0 \leq -c_s \lambda_s - k_s \mu_s + x_s p_s + r_p \lambda_s - r_s \lambda_s - r_p \\ \left[\beta \leq \frac{-[c_s \lambda_s + k_s \mu_s - p_s x_s - r_p \lambda_s + r_s \lambda_s + r_p]}{(-1 + \lambda_s)} \right]: 0 < \lambda_s \\ \left[\frac{-[c_s \lambda_s + k_s \mu_s - p_s x_s - r_p \lambda_s + r_s \lambda_s + r_p]}{(-1 + \lambda_s)} \geq \beta \right]: 0 > \lambda_s \\ []: \text{otherwise} \end{array} \right.$$

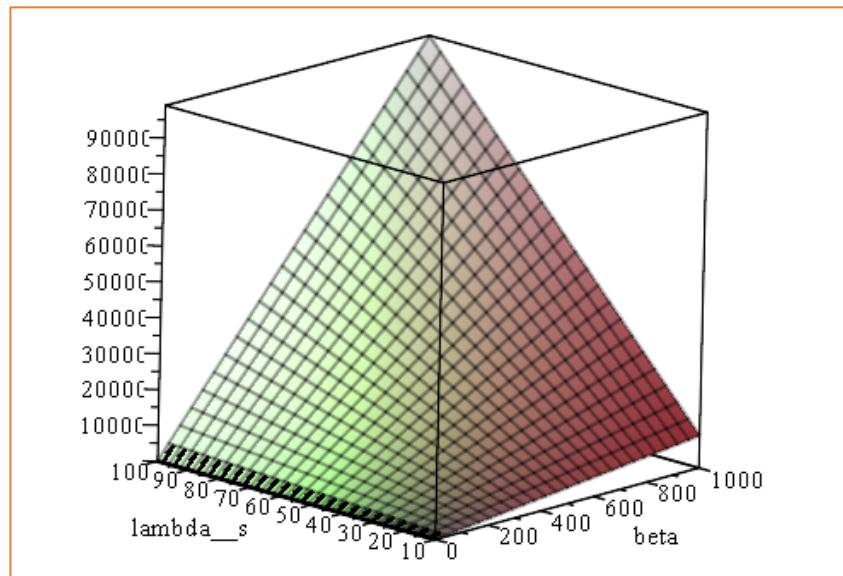


Figure 13: β and the number of patients with public healthcare insurance

When a patient with a public insurance is sent for treatment to a private hospital, it means that the public healthcare insurance company pays for treatment. The fact that the public healthcare insurance company is a nonprofit organization should not harm the institution as well as not profit. This constraint equation is expressed as:

$$\lambda_p r_p + (1 - \lambda_s)\beta + (1 - \lambda_s)c_p + \lambda_p c_p + (\mu_p + 1 - \mu_s)k_p \leq x_p p_p \quad (37)$$

▪ **Mathematical expansion of the β :**

$$\left\{ \begin{array}{l} [\beta = \beta]: 1 - \lambda_s \text{ and } [\beta = \beta]: 0 \leq -c_s \lambda_s - k_s \mu_s + x_s p_s + r_p \lambda_s - r_s \lambda_s - r_p \\ \left[\beta \leq \frac{-[c_s \lambda_s + k_s \mu_s - p_s x_s - r_p \lambda_s + r_s \lambda_s + r_p]}{(-1 + \lambda_s)} \right]: 0 < \lambda_s \\ \left[\frac{-[c_s \lambda_s + k_s \mu_s - p_s x_s - r_p \lambda_s + r_s \lambda_s + r_p]}{(-1 + \lambda_s)} \geq \beta \right]: 0 > \lambda_s \\ []: \text{otherwise} \end{array} \right.$$

The relationship between the reimbursement that private health insurance companies will pay to private hospitals and the amount they will pay to public insurance β should be balanced. This balance will ensure that private health insurance institutions will not suffer any loss.

$$\beta = r_p \quad (38)$$

Private insured customers and the number of treated patients is formulated as:

$$x_p p_p - \mu_p r_p \geq 0 \quad (39)$$

Generally, the patient satisfaction constraint is measured by the waiting time which is confronted with the insurance premium or co-payment in hospitals. Normally, whereas the private insurance premium's cost is more expensive than the public insurance premium; correspondingly the patient spent more time to see providers in public hospitals. The number of customers, the arrival, and the processing rate constraint in private and public hospitals is defined in equations 13 and 19. In this case, the relationship between hospitalization rates of customers with both private and public healthcare systems is shown in the following equation 40.

$$\lambda_s + \lambda_p \leq x_s, x_p \quad (40)$$

Considering high waiting time in public health system and low capacity of private health system are mainly triggered to build a new model for both health systems. In the developed optimization model, the objective function must be maximized so that the revenues of private health insurance companies are not negatively affected. The objective function equation is expressed as;

$$Expected Rev_p = max \sum [x_p p_p - (1 - \lambda_s) \beta - \lambda_p r_p] \quad (41)$$

Subject to 36, 37, 38, 39, and 40.

1.4. Computational Results

Presenting some numerical examples for each developed model are discussed in this section. Results of numerical example provided that our models are validate and run correctly.

1.4.1. Applications of Optimization Models in Monopoly Healthcare System

In this section, the results of the components of both the public and private healthcare systems are examined as monopoly.

1.4.1.1. Monopoly Public Healthcare System

Created a heuristic optimization model for monopoly of public healthcare system is considered the waiting time that is aimed to minimize. However, the waiting time is based on reimbursement and the cost of treatment a patient dependently.

1.4.1.1.1. The first objective function of the Public Healthcare System

In a public-owned hospital, the values below which a patient's treatment cost is minimized with a limit in the decision variables are indicated in the Table 2 below. The following warning was issued while solving; limiting number of major iterations has been reached.

Table 2: Results of the first objective function of the Public Healthcare System

<i>Cost</i>	\$169.05507
c_s	\$53.52301
k_s	\$69.97034
p_s	\$72.21903
r_s	\$422.24467
x_s	57.425.567
λ_s	0.40037
μ_s	0.492556
<i>Average Waiting Time</i>	19.6650 min

In a public-owned hospital, the values below which a patient's treatment cost is minimized without a limit in the decision variables are indicated in the table below. However, if the minimum cost is achieved, a patient's waiting time in the hospital is at least twenty

minutes. However, this waiting period will increase even more with the increase in the proportion of patients and the prolongation of the treatment period.

1.4.1.1.2. The second objective function of the Public Healthcare System

The second objective function of the public healthcare system is to minimize the waiting time of the patients. There is no limit to the decision variables in this model (Table 3).

Table 3: Results of the second objective function of the Public Healthcare System

<i>Objective Value</i>	17.7072 min
c_s	\$48.51578
k_s	\$64.48436
p_s	\$95.85507
r_s	\$163.02805
x_s	8.085.464
λ_s	36.34692/day-1.51455/hr
μ_s	117.668/day-4.902/hr
<i>Cost</i>	\$246.89886

The relationship between the rate at which the patient arrives at the hospital and the time required for treatment appears to be inversely proportional is shown in Figure 14.

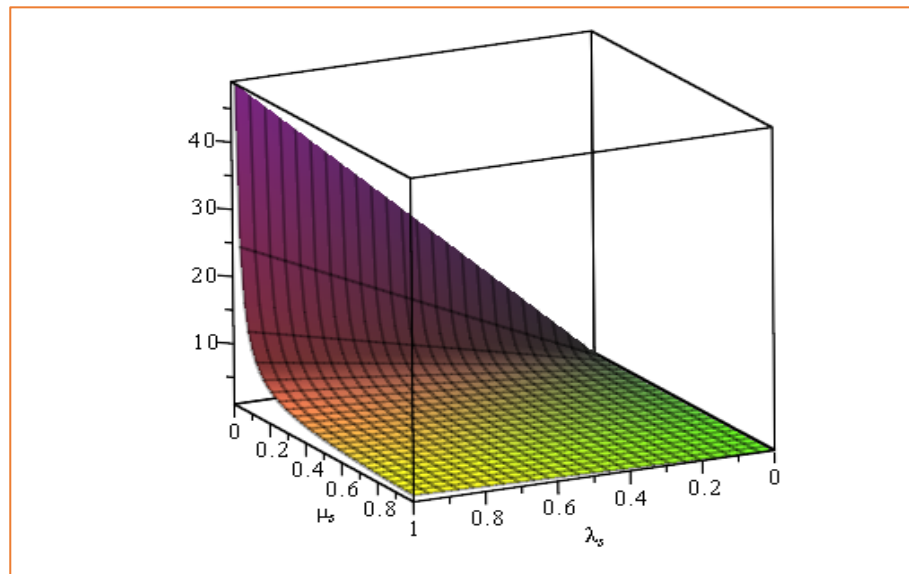


Figure 14: Waiting time in Monopoly System for Public Health

In the two optimization models developed for the public health system, the best

results were obtained without any limits being placed on the decision makers. When the optimum results are taken into consideration, it has been calculated which range of the values of the decision variables should be.

Table 4: The range of values for variables of the Public Healthcare System

c_s	[\$48.51578 ₂ ...\$53.52301 ₁]
k_s	[\$64.48436 ₂ ...\$69.97034 ₁]
p_s	[\$72.21903 ₁ ... \$95.85507 ₂]
r_s	[\$163.02805 ₂ ...\$422.24467 ₁]
x_s	[57.425567 ₁ ...80.85464 ₂]
λ_s	[0.40037hr ₁ ...1.51455hr ₂]
μ_s	[0.492556hr ₁ ...4.902hr ₂]
<i>Cost</i>	[\$169.05507 ₁ ...\$246.89886 ₂]
<i>Average Waiting time</i>	[17.7072min ₂ ...19.6650min ₁]

Note
₁-Results of the first optimization model,
₂-Results of the second optimization model.

Table 2 shows that there are three major decision-making variables that concern the patient. If the average waiting time of the patients is to be reduced to 18.68 minutes, the average co-payment amount to be paid by the patients or the health insurance clients is \$51.02 and the amount to pay for the insurance premium is \$84.04 averagely. Only the co-payment charge for these amounts is encouraging some patients to take advantage of the private health system.

Proof: If the decision variables are p_s , λ_s , and μ_s in the public healthcare system, the relationship between the waiting time of a patient and is given in **Table 5**. If the value of p_s is between \$100 and \$499, then the r value is at least \$501. Otherwise the model is unsolvable.

Table 5: The range of values for decision variables p_s , λ_s , and μ_s

Iterations No	Decision Variables			Objective Function	NLP Status
	p_s	λ_s	μ_s	Waiting Time	
-	\$100	-	-	-	Infeasible
26	\$150	0.15	0.85	0.8235	Feasible
26	\$200	0.20	0.80	0.8000	Feasible
26	\$250	0.25	0.75	0.7500	Feasible
26	\$300	0.70	0.30	0.5716	Feasible
27	\$350	0.35	0.65	0.4610	Feasible
27	\$400	0.40	0.60	0.3330	Feasible
27	\$450	0.45	0.55	0.1818	Feasible
27	\$499	0.49	0.51	0.0392	Feasible
27	\$500	0.50	0.50	-	Infeasible

Note: Lingo Optimization Software Output

1.4.1.2. Monopoly Private Healthcare System

The model is run for private monopoly health system that gives delivery to only private insurer patients. This model's objective function is aimed to maximize expected revenue and waiting time is assumed very low.

In the private health sectors expected revenue of \$42250 when a without limit is placed on the decision variables to capture the maximum income ratio. This amount is caught by treating very few patients and without waiting for the patient to wait. To achieve a positive result, the number of patients treated should be high and the duration of treatment required should be minimal. This situation is shown in **Table 6**.

Table 6: Unconstrained Monopoly Private Healthcare System

<i>Objective Function</i>	\$ 42,250.00
k_p	\$ 50.00
c_p	\$ 50.00
r_p	\$ 1000.00
r_p	-
x_p	-
λ_p	0.1000
μ_p	0.1000
<i>Average waiting time</i>	8.0000 min

When the constraints are taken into consideration, the values of the decision variables change, but also the income of the private health sector changes and its expected revenue is \$64842.6. The new values of the objective function and decision variables are shown in **Table 7**.

Table 7: Constrained Monopoly Private Healthcare System

<i>Objective Function</i>	\$ 64,842.56
k_p	\$150.00
c_p	\$ 50.00
r_p	\$ 1000.00
r_p	\$ 98.97
x_p	-
λ_p	0.0149
μ_p	0.01
<i>Average waiting time</i>	4.6451min

Scenarios were created taking into consideration the current decision variables. The values of the other decision variables are fixed to determine the limit of a selected decision variable. It is examined how these values affect the objective function value.

1.4.1.2.1. Scenario 1: r_p unknown

r_p unknown and $r_p \geq 0, c_p, k_p, p_p, x_p, \lambda_p, \mu_p$ variables are constants, values are shown in Table 8.

Table 8: Scenario 1 - unknown r_p

k_p	\$150.00
c_p	\$50.00
r_p	\$1.00<...<1,000.00
p_p	\$100.00
λ_p	0.1000
μ_p	0.1000
x_p	100
<i>Waiting Time</i>	8.0000 min
<i>Profit</i>	\$ 32,249.90

When the table are examined, the patient remains steady when the number of patients spent for treatment reaches a certain number. In this case, although the number of patients does not

increase, the waiting time of the patient increases with the increase of the treatment duration.

1.4.1.2.2. Scenario 2: k_p unknown

k_p unknown and $k_p \geq 0, c_p, r_p, p_p, x_p, \lambda_p, \mu_p$ variables are constants, values are shown in Table 9. It is seen that by decreasing the k_p value according to the first scenario and increasing the objective function value without changing the waiting time.

Table 9: Scenario 2 - unknown k_p

k_p	\$ 50.00
c_p	\$ 50.00
r_p	\$ 1,000.00
p_p	\$ 100.00
λ_p	0.1000
μ_p	0.1000
x_p	100
<i>Waiting Time</i>	8.0000 min
<i>Profit</i>	\$42,250.00

The table in Scenario 2 have the same characteristics as the table in Scenario 1. It is observed that the cost of treatment has not changed with the increase of the time required for the treatment. This situation is undesirable for healthcare providers.

1.4.1.2.3. Scenario 3: c_p unknown

c_p unknown and $c_p \geq 0, r_p, k_p, p_p, x_p, \lambda_p, \mu_p$ variables are constants, values are shown in Table 10. Although the patient has a small amount of fall in the waiting time, the objective function value is reduced according to the other scenario. In addition, the value of c_p appears to increase.

Table 10: Scenario 3 - unknown c_p

k_p	\$ 150.00
c_p	\$150.00
r_p	\$1,000.00
p_p	\$100 10.00
λ_p	0.0925
μ_p	0.1000

x_p	100
<i>Waiting Time</i>	7.071 min
<i>Profit</i>	\$ 26,750.00

In Scenario 3, the release of the co-payment amount, which is the most important cost factor in the healthcare system, leads to a decrease in the waiting time of the patients according to Scenario 1 and Scenario 2. It has been found that approximately 13.14% of benefits are provided for patients and healthcare facilities. However, the amount of prepayment or co-payment made to the hospital has increased by approximately \$100.00. The reason for this is that an agreement is made between the institutions providing private health care and the government and this amount is determined. In short, it is a question of overpaying the co-payment of a patient with a public health insurance and reducing the amount of co-payment that a patient with private health insurance must pay for treatment.

1.4.1.2.4. Scenario 4: p_p unknown

p_p unknown and $p_p \geq 0, r_p, k_p, x_p, \lambda_p, \mu_p$ variables are constants, values are shown in Table 11. The fourth scenario gives the most objective function value. Despite the increase in insurance premium, the waiting period in the hospital has decreased.

Table 11: Scenario 4 - unknown p_p

k_p	\$ 150.00
c_p	\$ 50.00
r_p	\$ 1,000.00
p_p	\$ 170.00
λ_p	0.0588
μ_p	0.0588
x_p	100
<i>Waiting Time</i>	4.7059 min
<i>Profit</i>	\$99,450.00

The amount of insurance premiums that are closely related to health insurance companies and customers is covered in scenario 4. When the table is followed, the average waiting time for the patient to be treated is great and there is a decline there. Compared to the other scenarios, Scenario 4 appears to benefit 69.9% of Scenario 1 and 2, and 13.14%

of Scenario 3 in terms of both patient and health care providers. The negative side of this scenario seems to be an average increase of \$70.00 in the amount that customers have to pay to have health insurance. The results of the monopoly private health system in optimization models were compared. The maximum, minimum and average values of the results obtained in the optimization models are calculated.



1.4.1.2.5. Comparison of Scenarios

Table 12: Monopoly Private Health Providers' Outputs

	Decision Variables	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Maximum	Minimum	Average
Optimum values	k_p	\$150.00	\$ 50.00	\$ 150.00	\$ 150.00	\$ 150.00	\$ 50.00	\$ 125.00
	c_p	\$50.00	\$ 50.00	\$150.00	\$ 50.00	\$ 150.00	\$ 50.00	\$ 75.00
	r_p	>\$1.00 <1,000.00	\$ 1,000.00	\$1,000.00	\$ 1,000.00	\$ 1,000.00	\$ 1,000.00	\$ 1,000.00
	p_p	\$100.00	\$ 100.00	\$100 10.00	\$ 170.00	\$ 170.00	\$ 100.00	\$ 117.5.00
	λ_p	0.1000	0.1000	0.0925	0.0588	0.1000	0.0588	0.0851
	μ_p	0.1000	0.1000	0.1000	0.0588	0.1000	0.0588	0.0836
	x_p	100	100	100	100	100	100	100
	Waiting Time	8.0000 min	8.0000 min	7.071 min	4.7059 min	4.7059 min	8.0000 min	6.944 min
	Profit	\$ 32,249.90	\$42,250.00	\$ 26,750.00	\$99,450.00	\$ 99,450.00	\$ 26,750.00	\$ 50,174.90
Improvements	k_p	16.66 _l %	60.00 _p %	16.66 _l %	16.66 _l %	\$ 150.00	\$ 50.00	\$ 125.00
	c_p	33.33 _p %	33.33 _p %	100 _l %	33.33 _p %	\$ 150.00	\$ 50.00	\$ 75.00
	r_p	Stable	Stable	Stable	Stable	\$ 1,000.00	\$ 1,000.00	\$ 1,000.00
	p_p	14.89 _p %	14.89 _p %	14.89 _p %	44.68 _l %	\$ 170.00	\$ 100.00	\$ 117.50
	λ_p	14.89 _l %	14.89 _l %	14.81 _p %	44.68 _p %	0.1000	0.0588	0.0851
	μ_p	16.32 _l %	16.32 _l %	9.62 _l %	42.26 _p %	0.1000	0.0588	0.0836
	x_p	Stable	Stable	Stable	Stable	100	100	100
	Waiting Time	15.207 _l %	15.207 _l %	1.828 _l %	32.230 _p %	4.7059	8.0000 min	6.944 min
	Profit	35.725 _l %	15.794 _l %	46.686 _l %	98.206 _p %	\$ 99,450.00	\$ 26,750.00	\$ 50,174.9.00

Note 1: Improvements are calculated according to the average value.

Note 2: p = profit, l = loss.

As a result of these scenarios, not only patients with private health insurance but also patients with public healthcare insurance are taking this system. There is not just one scenario that gives the best result in the direction of these results. Scenarios differ in terms of the value of the decision variables in the scenario. For example, scenarios 1 and 4 provide the least amount of co-payment paid to the hospital. The number 2 is the scenario that gives the least amount of patient treatment cost.

There is a difference in the comparison of the amount of reimbursement between the scenes. In other scenarios except Scenario 1, the reimbursement amount is \$1000. However, the amount of reimbursement in Scenario 1 is between \$1 and \$1000. This situation falls to \$275 when viewed in the monopoly system.

The rates of patients arriving at health facilities and the amount of time required for treatment are the same in all scenarios. In the same way, 100 people with private health insurance were taken into consideration. The average amount of premiums that customers need to pay to have health insurance is \$117,5. As a result of all these comparisons, it is scenario number 4 that the waiting time is low in terms of the patient as well as the maximum income in terms of health institutions.

1.4.1.3. Monopoly Public Healthcare Funders Systems

If the public insurer does not make a profit, there is a negative direction with the cost of the high waiting time of the patients. At this point, the diversity shown by public insurance premiums can be contracted with some private healthcare providers and some patients can be treated in contracted hospitals. However, the cost of annual patient treatment should not exceed the annual income of citizens with public insurance (Table 13).

Table 13: Monopoly Public Healthcare Funders' Outputs

<i>Objective Function</i>	\$ 1235.20
c_s	\$ 53.52
k_s	\$ 70.00
p_s	\$ 73.06
r_s	\$ 352.92

x_s	65.260
λ_s	0.1000
μ_s	0.2500
<i>Average Waiting time</i>	15.0001 min

1.4.1.4. Monopoly Private Healthcare Funders

In view of this optimization model, private health insurance requires less reimbursement to increase annual income. At this point, private health care providers will not accept this agreement. Private health insurance companies are required to have an agreement with public hospitals. This will have a negative impact both on patients with private health insurance and on public hospitals. Private health insurance companies have to push some limits. For example, it is necessary to increase the amount of reimbursement to be paid to hospitals by increasing insurance premiums.

Another limitation is that the amount of reimbursement to be paid to the hospital should not be less than the cost of the treatment of the patient. Otherwise, the incomes of private hospitals will be reduced. When some limits are taken into consideration, the values given in the Table 14 below are obtained.

Table 14: Monopoly Private Health Funders' Outputs

<i>Objective Function</i>	\$ 442,948.59
c_s	\$ 220.00
k_s	\$ 170.00
p_s	\$ 900.00
r_s	\$ 300.00
x_s	0.2000
λ_s	0.9900
μ_s	100.1
<i>Average Waiting time</i>	15.95min

1.4.2. Applications of Optimization Models in Network Health System

In the previous section, we examined two different healthcare systems individually. In this section, we examine how the healthcare systems affect the aims of the two healthcare systems as a result of the interaction. Two main situations are taken into account in the interaction of healthcare systems. These are health care providers and healthcare

fundlers with patients waiting time.

1.4.2.1. Networks between Healthcare Providers

How the objective functions of the private health sector and the public health sector changed as a result of the interaction between the private health system and the public health system.

1.4.2.1.1. Private Healthcare System

The most important purpose of the private health system is to increase the annual income to the maximum level without affecting patient waiting time. Optimum results are given in the Table 15.

Table 15: Networks between Healthcare Providers: Private Health System

<i>Objective Function</i>	\$ 13,200.00
k_p	\$ 300.00
c_p	\$ 200.00
r_p	\$20,00.00
λ_p	0.1000
μ_p	0.1000
λ_s	0.2000
μ_s	0.1000
<i>Average waiting time</i>	6.0000 min

1.4.2.1.2. Public Healthcare System

The first data obtained without constraints of the objective function of the public healthcare system are given in the Table 16 below.

Table 16: Networks between Healthcare Providers: Public Health System

<i>Objective Function</i>	9.5833 min
k_p	-
c_p	-
r_p	-
λ_p	0.2000
μ_p	0.2000
λ_s	0.2000
μ_s	0.6000
<i>Average waiting time</i>	-

1.4.2.2. Networks between Healthcare Funders

The issue to be considered in this section is that a patient with public healthcare insurance can be treated in a private hospital. To be able to do this, some constraints must be recognizable. For example, there should be a special rate between private health insurance companies and public-owned healthcare companies. That is, private health insurance companies have to pay for the public healthcare insurance institution as if the patient had private health insurance that goes to the private hospital. The public healthcare insurance should be provided not to loss by considering the reimbursement paid to the private hospital. Taking these constraints into account, the change in annual revenues has been shown in the monopoly system of private health insurance companies.

Table 17: Outputs of the Monopoly Public and Private Healthcare Funders

Variables	Private	Public
c_s	\$53.02	\$ 48.00
k_s	\$122.90	\$ 64.00
p_s	\$350.00	\$ 83.93
r_s	\$275.00	\$ 163.00
x_s	100	57.64
λ_s	0.0475	0.0475
μ_s	0.1589	0.1344
<i>Average Waiting Time</i>	9.0500min	8.0600min
<i>Objective Function</i>	\$ 34,730.00	-

1.5. Interpretation of Optimization Outputs

The results of the optimization models developed for health systems, financial affairs have been discussed in this section to provide the best decision in terms of the healthcare components. Firstly, I need to distinguish components of healthcare as patients, providers, governments, and funders. Optimization models were developed by taking care of each healthcare component. Some specific constraints of these models have been identified and added. Decision variables in both objective functions and constraint functions for healthcare system components play an important role.

With this study, it is discussed which health system will give better results. In short, certain features or constraints of two systems are determined and compared. There are three points on this part of the thesis. These are patients, providers, and funders. It has been tried to determine how these three factors are affected by the optimization models established. From the point of view of the patient or the customer with health insurance, it has been tried to determine which system is to be faded. When the other components are taken into consideration, the treatment quality and the way the fees are affected by the patients are separately examined.

Having more than one component in the health system causes more than one purpose function. It should be noted that while one component achieves the desired result for the objective function, the change in the results of the objective functions of the other components is inevitable. From this point of view, it is observed that the results obtained are close to optimum values. So, the results are feasible and are within the feasible region.

This application has many decision variables for each health component. These are cost of treatment, reimbursement, co-payment, number of customers with health insurance, rate of patients coming to the hospital and treated. Taking these decision variables into consideration, the best solution for each health combination will be obtained. For example, the waiting period in terms of patients, the annual income from the hospital point of view, no loss to the state or government, and finally the premium amounts in terms of healthcare insurance institutions and the number of insured citizens or customers. By considering these footnotes, I analyzed healthcare components in two main sections which are the interaction between healthcare systems and as monopoly healthcare system. At the bottom of each system, evaluations were

made in terms of healthcare components.

1.5.1. Monopoly System between Healthcare Components

In this section, the healthcare system is examined as monopoly. Both the components of the private and the public healthcare system have been created and the feasible results have been obtained. These results were taken into consideration in the terms of patients, state or government, funders and providers, which are common components of healthcare systems, and the values of decision variables belonging to these components were determined. This section has been examined in two parts. These are public and private healthcare systems.

1.5.1.1. Public Healthcare System

The results of the decision variables obtained in this section are taken as the average of the values in Table 4. There are lower and upper limit values of decision variables in this Table 4. The reason for assessing the mean outcome of these values is due to changes in rates of patient admission and treatment time rates. It is not possible for these two variables to have a certain rate. Another decision differs in value from time to time. This decision variable is the number of customers with health insurance. If the monopoly system has a health insurance policy, the patient can receive treatment services only in that kind of hospital. While a patient with public healthcare insurance is only served in public -owned healthcare institutions, a patient with private health insurance is only served in private health centers. However, insurance premiums paid by customers with any health insurance and the amount of reimbursement the insurance companies pay to the hospital are effective on the customers. For this reason, it is inevitable to see a change in the number of customers with health insurance. When all these reasons are taken into consideration, averages of the lower and upper limits of the decision variables of the public health system are taken.

What should be considered in the public healthcare system is how the components of the government are affected. When the constraints of the created optimization models are taken into consideration, the feasible values of decision variables are calculated. The most important of these variables is the number of patients coming to the hospital. Because this value negatively affects the public healthcare expenditures which are included in the constraints because of patient waiting time.

In this system, patients only have public healthcare insurance and prefer public hospitals for treatment:

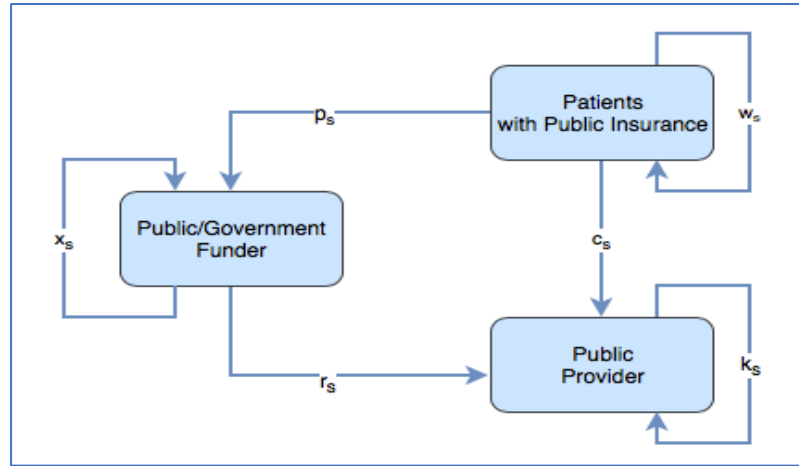


Figure 15: Interaction between Healthcare Components: Public Healthcare System

Four different factors have been considered in this system when optimization models are created. It has been observed that the decision variables are feasible in terms of patient, provider, funders and government.

1.5.1.1.1. Feasible results for the Patients

The most important component in the center of the health system is the patient. Optimization models and constraint equations have been established in both health systems considering this factor.

Table 18: Feasible results for the Patients

Decision Variables	Average Values
c_s	\$51.019
p_s	\$84.05
<i>Average Waiting time</i>	18.68 min

Table 18 shows that there are three major decision-making variables that concern the patient. If the waiting time of the patients is to be reduced to 18.68 minutes, the co-payment amount to be paid to the patient by the patients or the health insurance clients is 51 dollars and the amount to pay for the insurance premium is 84 dollars. Only the co-payment charge for these amounts is encouraging some patients to take advantage of the private health system.

1.5.1.1.2. Feasible results for the Providers

Four different decision variables have been taken into account when examining the public healthcare system in terms of providers (See Table 19)

Table 19: Decision Variables Average Values for Providers

Decision Variables	Average Values
k_s	\$67,22273
c_s	\$51.019
λ_s	0.9573
μ_s	2.6972

The average cost of a patient to treat a patient is \$67.20. Likewise, when paying attention to the patient, the co-payment amount the patient will pay to be treated is \$51.00. In the previous section, it seems that the co-payment amount is the same. The proportion of patients coming to the hospital seems to have reached the minimum level required to treat a patient. It is understood that these results are approaching the optimum value.

1.5.1.1.3. Feasible results for the Funders

In this section, information about the public healthcare insurance system is discussed. The decision variables that directly affect the health insurance are the amount of insurance premiums paid by customers who want to have health insurance, the amount of reimbursement the health insurance company will pay to the hospital, and the number of customers who want to have health insurance. Since the public healthcare insurance institution is a nonprofit organization, it is not required to make any profits or loss.

Table 20: Decision Variables Average Values for Funders

Decision Variables	Average Values
p_s	\$84.05225
r_s	\$292.64
x_s	69.14

Where the proportion of public insured patients with multiply the insurances' premiums

must be:

$$x_s p_s - \lambda_s r_s \geq 0$$

Result: \$3,200.50.

1.5.1.1.4. Feasible results for the Government

The public healthcare system expected profit must be nonnegative and is computed since $\lambda_s(r_s + c_s) - \mu_s k_s \geq 0$ (Andritsos & Tang, 2014). The constraint of the hospital's reimbursement and the unit cost for treating a patient are formulated as:

$$\lambda_s(r_s + c_s) \geq \mu_s k_s$$

Other decision variables included in the above constraint equation include the amount of co-payment the patient will pay to the hospital, the rate of patients coming to the hospital, and the time needed to treat the patient. It has been observed that these decision variables are not harmful to the public health system in accordance with the results obtained in other sections.

1.5.1.2. Private Healthcare System

When examining the private healthcare system alone, only those who have private health insurance need to be treated in private health care providers (Figure 16). Two kinds of results are obtained with the operation of mathematical model related to private health service in this frame. The most important factors affecting these results are constraint equations. The goal is to handle constraints as limits or to process them unlimitedly to achieve the function. However, how to determine the limits when the restrictions are taken into account are given in section 4. In this section, only two types of results are discussed and interpreted.

When the results are examined, the value of the objective function is reduced in non-limit constraints. However, it is observed that a certain number of patients have come to be treated and that the goal function has increased. In addition, the waiting time for private health care facilities for patients wishing to be treated seems to be decreasing. However, increasing the cost of patient treatment is a negative situation (See Table 21).

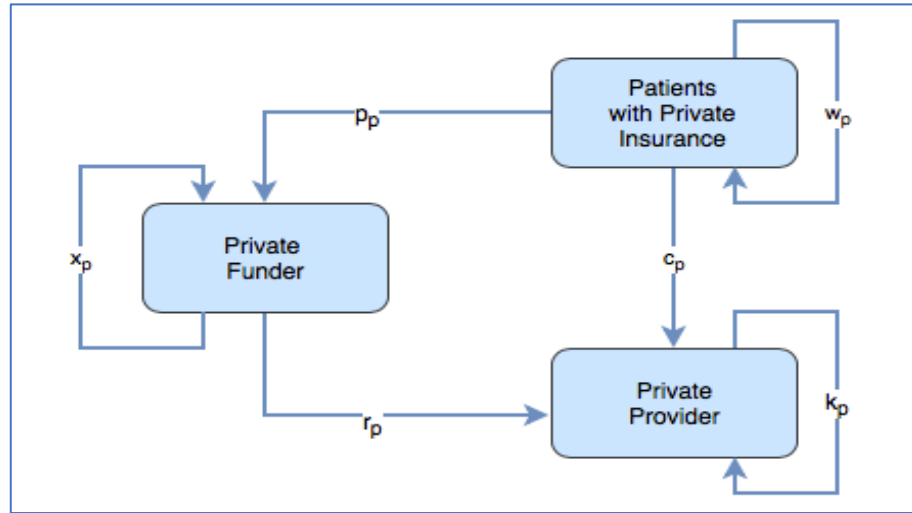


Figure 16: Interaction between Healthcare Components: Private Health System

Table 21: Decision Variables Without With

Decision Variables	Unconstrained	Constrained
Objective Function	\$ 42,250.00	\$ 648,422,360.56
k_p	\$ 50.00	\$150.00
c_p	\$ 50.00	\$ 50.00
r_p	\$ 1,000.00	\$ 1,000.00
λ_p	10.00	10.00
μ_p	10.00	66.67
x_p	—	100.00
Average Waiting Time	8.00 min	4.645 min

In this section, which is examined in two different areas, there are differences in other decision variables. Patient waiting times have been observed to decrease with increasing patient treatment cost. This trend is expected. The other changing decision variable is the number of customers with private health insurance. The system recognizes the number of customers with health insurance unlimitedly while there are no constraints related to the objective function. However, the number of customers who have health insurance has been determined as 100 when the restrictions related to this system are added. A certain proportion of the number of customers and the proportion of patients required for treatment also show the quality of the health care provided. As a result, it can be said that the annual income obtained is increased by 10000 times. It is understood that the result obtained with the number of customers with unlimited health insurance is 10,000 and above.

1.5.2. Collaboration between Healthcare Components

In the previous sections of this section, the health system was monopoly examined and interpreted over the values of decision variables and objective functions. However, in this section, it is observed how the decision variables get a result as the result of the interaction between the health systems.

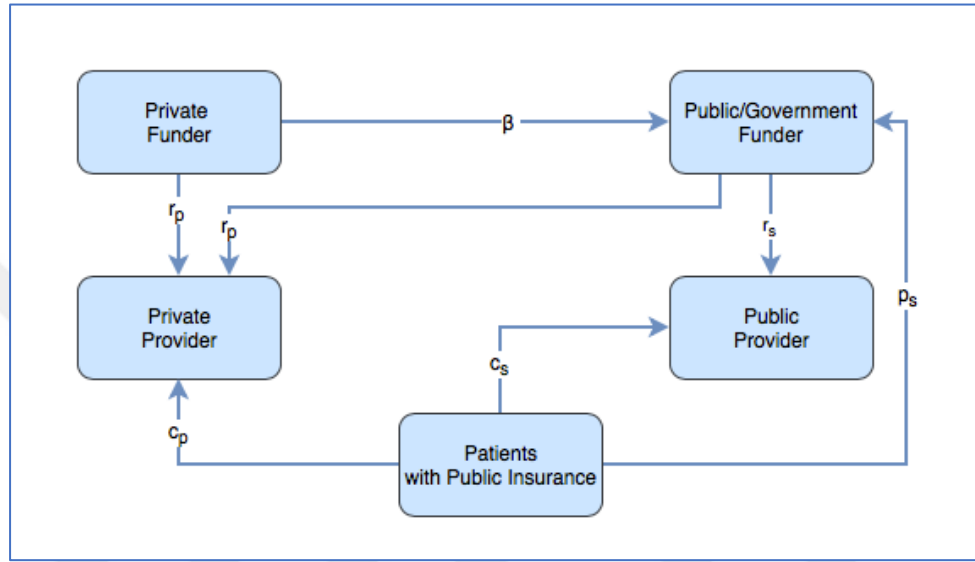


Figure 17: Interaction between Healthcare Components: Public and Private Funders

When the decision variables are taken into consideration, the objective functions of the components of each health system are formed separately (see Table 22).

Table 22: The feasible output of Healthcare Components

Decision Variables	Private	Public	Private Funders	Public Funders
Objective Function	\$ 13,200.00	9.5833 min	\$ 34,725.00	8.06min
k_i	\$ 300.00	—	\$122.90	\$ 64.00
c_i	\$ 200.00	—	\$53.02	\$ 48.00
r_i	\$2,000.00	—	\$275.00	\$ 163.00
p_i	—	—	\$350.00	\$ 83.903
λ_i	10/hr. or 0.2/hr.	0.2/hr.	21.04/hr.	21.04/hr.
μ_i	10/hr. or 0.2/hr.	0.6/hr. or 5/hr.	6.29/hr.	7.44/hr.
x_i	100.00	69.14	100.00	57.95
Average waiting time	6.00 min	—	9.05 min	—

Note $i = \{s, p\}$

This interaction allows the following expressions to be answered. These statements include;

- ☐ The waiting time of the patients who want to be treated in the public healthcare establishment,
- ☐ Interaction of health systems and annual incomes of private health system organizations,
- ☐ The waiting time of the patients who want to be treated in the private health institution,
- ☐ Governments that meet the majority of the costs of treatment in the public health system are not harmed,
- ☐ The amount of insurance premiums to be paid by patients who have public health insurance,
- ☐ The amount of insurance premiums to be paid by patients with private health insurance,
- ☐ The fee and waiting time for a patient with a public healthcare insurance to pay for treatment at private health institutions,
- ☐ Remuneration and waiting time for a patient with a private health insurance to be paid for treatment at public healthcare institutions,
- ☐ In order for a patient with a public insurance to be treated in private healthcare institutions, the amount of reimbursement required for the public healthcare insurance to be paid to the private health institution,
- ☐ In order for a patient with a private health insurance to be treated at public health institutions, the amount of reimbursement for private health insurance must be paid to the public health institution,
- ☐ To have special discounts for the government to cover the cost of treatment of patients with public healthcare insurance to increase the annual income of the private health institution.

As a result, it is seen that the values of the decision variables belonging to the healthcare system are closer to each other. It is determined that the waiting times of patients who want to be treated are close to each other in both private and public healthcare institutions. In the public health care system, the waiting time for patients has decreased from 19.665 minutes to 9.5833 minutes (see Figure 18). However, it is determined that the amount to be paid to the public healthcare insurance has increased from \$50.00 to \$83.903 (see Figure 19). These pricing schemes show the minimum payable amounts.

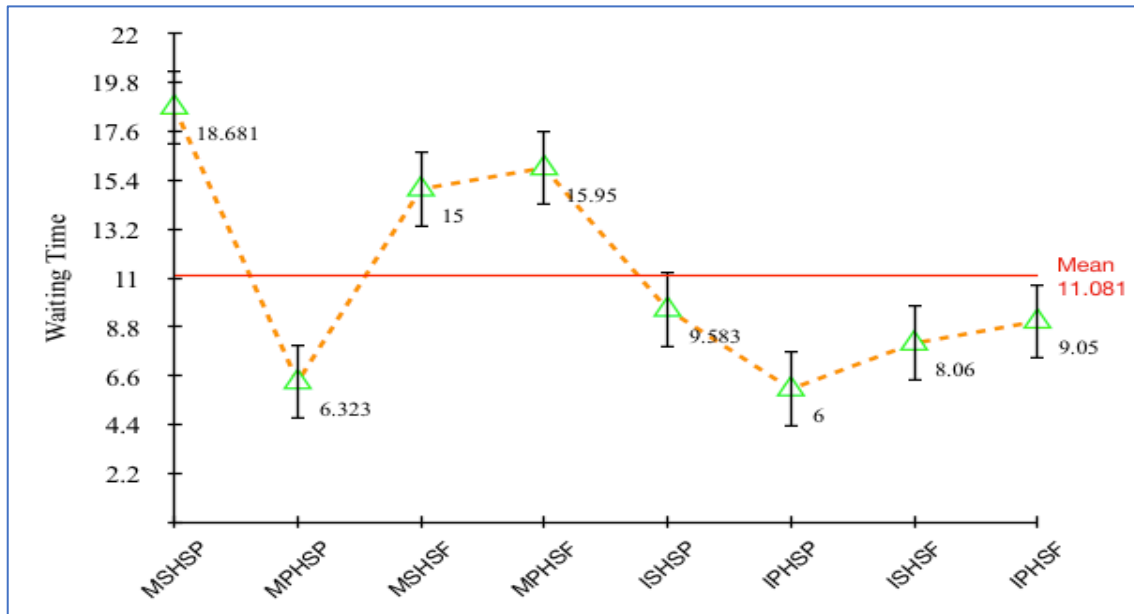


Figure 18: Waiting Time Level



Figure 19: Insurance Premiums Levels among Healthcare Systems

When the scenarios of the monopoly of the private health system are examined, the average amount that a person will pay for private health insurance is \$117.50. In this case, those who should have private health insurance will have to pay at least \$350.00. With high health insurance premiums, both government and private health care institutions will be able to receive any kind of health care. It is seen that the amount of co-payments that a patient has to pay to the hospital for treatment in any hospitals is high in the private health system and this amount is reduced to a minimum level in the interactive health system (see Figure 20).

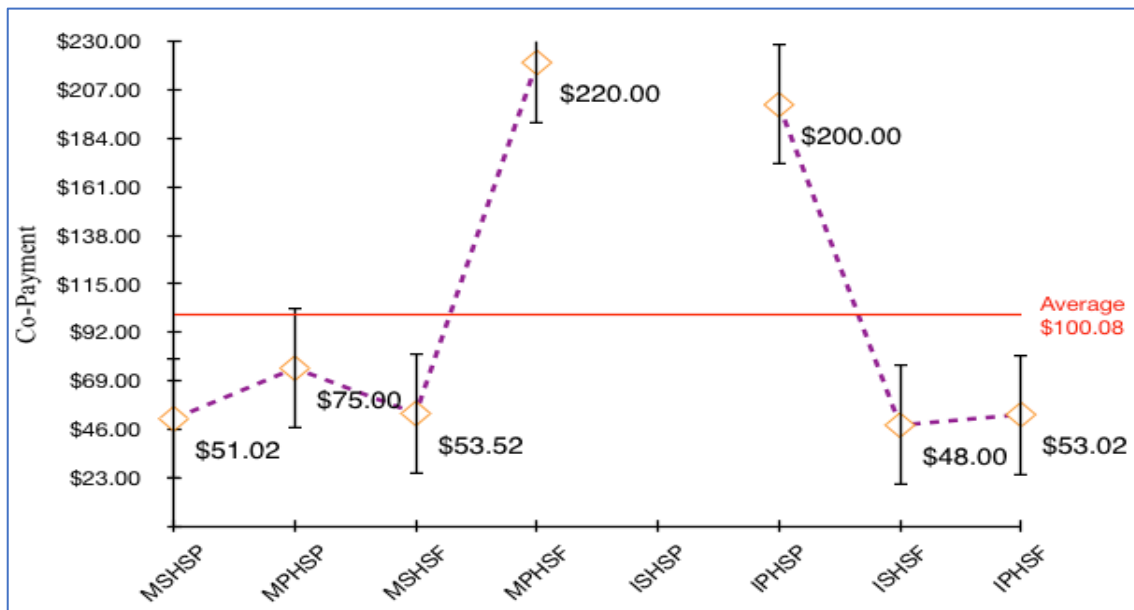


Figure 20: Co-payment Levels among Healthcare Systems

The greatest change in the transition of the healthcare system from the monopoly to the interactive system is seen in the amount of reimbursement. In particular, it has been found that the amount of reimbursement, which is a great cost for government, has decreased. The reimbursement rate in the private healthcare system drops from \$2,000.00 to \$163.00 (see

Figure 21).

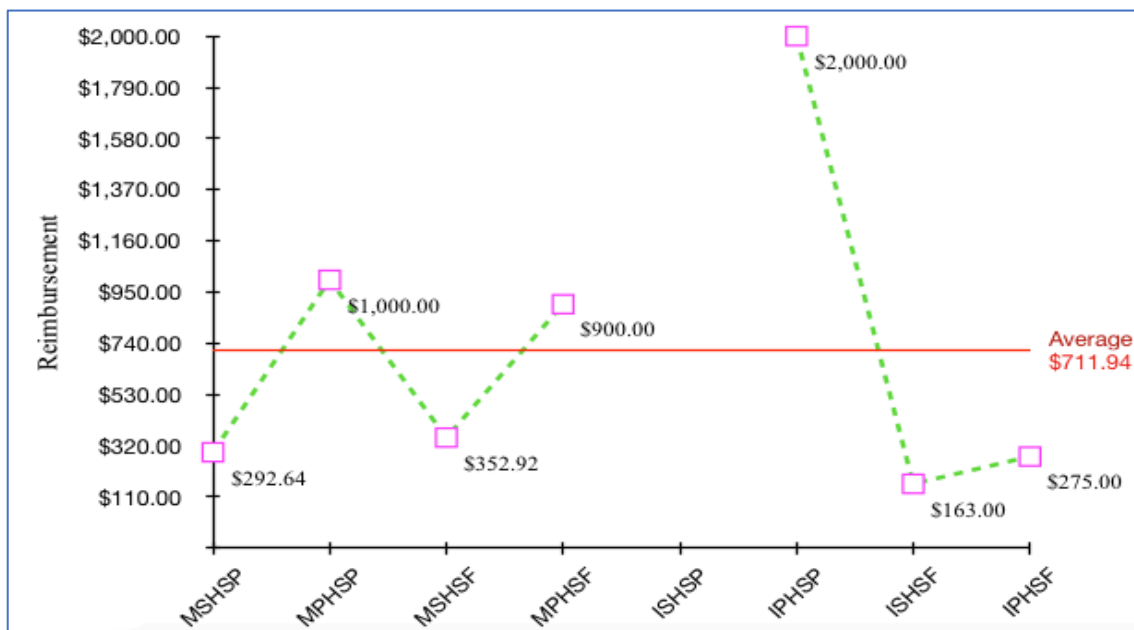


Figure 21: Reimbursement Levels Among Healthcare Systems



Figure 22: Treatment Cost Levels Among Healthcare Systems

The average cost of treatment for a patient is \$ 131.30. This value gives the average of the results obtained for all health systems. The highest treatment cost is \$ 300.00, while this value drops to \$ 64.00.

1.6. Conclusions of the Component of Healthcare Systems

In industry or health environment, the main goal is to develop the potential quality for products, increase patient or customer satisfaction and system or resources of health facilities performance. Many companies lose profit due to wrong applications of methods. It causes defection of products or services.

In this research, health systems have been extensively examined and specific methods have been developed to solve important problems. The best results were obtained for the main components of healthcare systems. Having many components in healthcare system makes a complicated problem; therefore, optimization technique is inevitable to overcome this complex health system. This study obviously shows that developing new optimization models provides tangible solutions for healthcare systems.

The main aim for this study is to increase the quality of the patient both in public and private healthcare sectors. Around the world, there are two types of problems that belong to these organizations. First, patients stay longer in public hospitals, so patient dissatisfaction and treatment costs are increasing. The second problem belongs to private health institutions. In this problem, the waiting time of the patients is low, and the cost is high. This means that patients need to pay a lot from their pocket to wait less. For this reason, the number of patients treated annually in private health institutions is decreasing. When these conditions are compared, it is seen that there is an imbalance. In order to create a balance between the public and the private health system, the best solutions have been obtained by creating optimization models with the scenarios provided. Optimization models that include scenarios in which the aim is achieved and that the winner who is not lost is within certain boundaries.

When these conditions are compared, it is seen that there is an imbalance. In order to create a balance between the public healthcare system and the private health system, the best solutions have been obtained by creating optimization models with the scenarios provided. Optimization models emphasize that scenarios in which the aim is achieved and that the winner who is not lost is within certain boundaries. These limits are:

- The number of patients treated by hospitals,

- The registration fee that the patient has to pay to the hospital,
- Patient treatment cost, The cost of the insurance to the hospital,
- Patient's monthly insurance premium indicated by the solution of the optimization models.

As a result, the parties that make up the health system have achieved positive results, especially for those in the center. With these results, it has benefited by not losing any sides of healthcare components. This method can be developed further because it is the first application in this area.



Chapter 2: Design of Experiment and Discrete Event Simulation

Section 1: Developing Optimization Models Using Simulation with Design of Experiment to Improve Quality of a Healthcare Facility

2.1. Introduction to Simulation with Design of Experiment in Healthcare

Nowadays, healthcare organizations have developed quality insights to better serve patients. There are two main reasons for this: increasing patient tolerance and reducing patient treatment costs. A number of methods have been tried to reduce hospital costs but there are common factors connecting these two reasons.

The first method is to control costs by reducing the length of stay of patients (LOS) (Iii, Hwang, & Nagarajan, 2001). The second one is, it is ensured that the cost of patient treatment is reduced in proportion to the decrease in patient waiting time. In order to achieve this, the existing resources in hospitals need to be managed properly. However, a health care provider needs a long time to manage the resources within it. Because the number of hospital resources constitutes the number of combinations. In a real situation, it is almost impossible to apply these combinations. This problem can only be overcome by combining the experimental design method and the simulation technique. By combining these two methods, the best and tangible results will be achieved in a very short time, which will help to increase the best service for patients and reduce the cost of patient treatment (Lin, 2008).

This paper has two major areas which are simulation technique and design of experiment (DOE) approach beside developed optimization models. Many companies have generally needed to use computer simulations in a wide range of area (Bates, Kenett, Steinberg, & Wynn, 2006). The reason behind that is the advantages this computer simulation obtains such as saving time, saving cost and changing resources easily for the industry. Especially, the healthcare area has spent much time to apply simulation model in their facilities in order to improve resources' capacity. However, using only simulation software is not enough to get accurate results. In the past, some researchers have tried some applications to a simulation model. These applications, conventional design methods, intent to improve the performances of goods (Park, Lee, Lee, & Hwang, 2006). However, these situations may not be valid to get healthy results. The main problems in many industrial environments to improve the quality of product and performances

are the necessity to succeed a target value and intercept a small variance (Ding, Lin, & Wei, 2004).

Healthcare structures have dynamic settings, multifaceted, and become large (Cabrera et al., 2011). Using simulation and DOE techniques help to cope with this system. Generally, all of healthcare providers such as government (state or public hospitals), private etc. try to reduce their expenses, idle resources which are physicians, nurses, exam rooms, administrators, etc., increase their performance, and minimize patient waiting time. However, changing resources of hospital obviously takes long time and very costly without using simulation and design of experiment. With the experimental design and optimization simulation technique, a 28% increase in patient outcomes and a 40% decrease in patient waiting time were thought to be due to optimum staff management (Ahmed & Alkhamis, 2009).

This research improves a new concept of DOE contains simulation experiment which utilizes the DOE. This research is different from other studies; is that the optimization models are derived from the simulation technique, but the optimization models need to be created in accordance with the information obtained as a result of the experiment design. Because, how the factors affect the response cannot be determined without experiment design. Furthermore, it is very difficult to determine by simulation how to determine how only the factors will affect the response, not the individual, but the interaction with each other. As mentioned, it is seen that the optimization models to be obtained are complex linear equations. Generated and gathered data from the simulation of the Flexsim Healthcare model, which was chosen to model this simulation because of its ease of use, for the DOE was optimized in Minitab Statistic Software which is used in the academic and industry area by researchers and companies to compare outcomes from these tools in order to show the results are accurate.

Generally, the scheduling problems which are appointment scheduling, operating room scheduling, workforce scheduling etc. were taken into account when the optimization method was applied in the healthcare area. Some studies have created optimization models without analyzing which hospital sources are more effective. Generally, when optimizing models are established, hospital resources are associated with patient waiting time (Feili, 2013). There are two main objectives of the developed optimization models in this research. These are treating more patients and reducing patient waiting time. However, to achieve these two goals, the capacity of existing hospital resources should be considered, and the duration of each treatment

should be considered. These factors constitute constraints of their function.

This paper is designed as follows: computer simulation is explained in Section 2. This section follows how the design of experiment is applied. In section 4, the optimization models are generated from the obtained data. Conclusively, Section 5 includes conclusions and future work of this research.



2.2. Simulation Model

2.2.1. Overview of Simulation Technology

The use of the simulation technique is based on the 1960s. It is because of the need for this technique to gain the loss from time and cost. The first application was made in the maritime sector, which was an oil carrier in the 1962s (Pidd, 2004). The literature shows that the areas where the simulation technique is used vary. The following Table 23 shows some scientific articles showing areas where the simulation method is used according to years.

The basic rules of the simulation technique are quite simple. The person who will create the simulation model first builds the model of the system it is interested in, writes the computer program of the simulation model (if there is no preset program), and executes the simulation model by making the changes that it wishes to make (Pidd, 2004).

Correct design of simulation experiments is a good technique to save time and cost by providing effective ways of estimating the effects of the simulation model on the responses of inputs (Kelton & Barton, 2003). Computer simulation methodology, involving large statistics information in order to have rational answers by data, is one of the most prevalent tools for quality engineering systems. Simulation operates complex variables and constraints to describe a system strictly (Montevecchi et al., 2007) Furthermore forecasting performances of systems, simulation likewise empowers projecting for future. The simulation model contributes a healthier understanding of the probable performance of the actual system if it is run precisely (Barton, 2001). As an analytical technique, simulation embraces systems and models of those systems (Kelton, 2004). Simulation models usually have many input factors and it is difficult to determine which of them is a significant influence on the responses (Law, 2014). The use of DOE with Computer Simulation allowed a better-organized analysis of the results from the simulation model to accomplish decision-making.

Table 23: Literature and Field Research Topics Citation

Literature and Field	Research Topics	Citation
Computer Language	Control and Simulation Language	(Buxton & Laski, 1962)
Computer Language	SIMULA: an ALGOL-Based Simulation Language	(Dahl & Nygaard, 1966)
Health	Applications of computer simulation in health care	(England & Roberts, 1978)
Thesis	Combined continuous/discrete system simulation by use of digital computers techniques and tools	(Cellier, 1979)
Food	Simulating Automated Food Plants	(Pidd, 1987)
Computer Language	Distributed Discrete-Event Simulation	(Misra, 1986)
Traffic	Microcomputer in Traffic Engineering	(Young, Taylor, & Gipps, 1989)
Health	Simulation Study of an Automated Guided-Vehicle System in a Yugoslav Hospital	(Čerić, 1990)
Food	Modelling Beverage Processing Using Discrete Event Simulation	(Harrell, 1993)
Transportation	Waterfront Capacity-Planning Simulations	(Heath, 1993)
Finance	Back-Office Process Management in the Financial Services- a Simulation Approach Using a Model Generator	(Davies, 1994)
Health	Using Simulation to Reduce Length of Stay in Emergency Departments	(McGuire, 1994)
Traffic	The Construction of an Object-Oriented Traffic Simulator	(Pidd, 1995)
Production	Application of discrete event simulation to the activity-based costing of manufacturing systems	(Spedding & Sun, 1999)
Telecommunication	Applications of business Process Simulation and lean Techniques in British Telecommunication PLC	(Dennis, King, & Hind, 2000)
Health	Using Monte Carlo Simulation to Assess the Value of Combination Vaccines for Pediatric Immunization	(Jacobson, Sewell, & Weniger, 2001)
Transportation	Simulation of Check-in at Airports	(Joustra & van Dijk, 2001)
Production	Discrete Simulation Development of a Proposed Shipyard Steel Processing Facility	(Williams, Finke, Medeiros, & Traband, 2001)
Health	Modelling the Public Health Response to Bioterrorism: Using Discrete Event Simulation to design Antibiotic Distribution Centers	(Hupert, Mushlin, & Callahan, 2002)
Production	Discrete Event Simulation: An Efficient Tool to Assist Shipyard Investment and Production Planning	(Matthias, Frank, Dirk, & Maximilian, 2004)
Health	Incorporating Discrete Event Simulation into Quality Improvement Efforts in Health Care Systems	(Rutberg, Wenczel, Devaney, Goldlust, & Day, 2013)

2.2.2. Establishment of Simulation Model for the Application

The records were composed of averages based on other raw data findings (see Table 24). These averages derived from many dissimilar references and generated a precise distribution for a computer simulation model. A large amount of data gathered from studies demonstrated to be more beneficial than the beforehand found means (Atalan, 2014; Atalan et al., 2013).

Table 24: Simulation Parameters

Parameters	Input Parameters
Arrival Distribution	Triangular Distribution
Resources	Clerk, Nurse, Physician, Triage and Exam Room
Processing Time	Exponential, Uniform, Beta and Weibull Distribution
Queue Discipline	FIFT (First-in First-Treatment)

By using the simulation models of any part of a hospital, the information of that part is obtained. The emergency section of a small hospital activates around the clock (Altioek & Melamed, 2007). It is operated by two clerks at the reception office, and three medical doctors on the locations, supported by three nurses, one for each physician. The department of the hospital has two triage sections for the nurses to serve patients. Figure 23 represents a plan of the patient movement chart in the part of a hospital, from arrival to release.

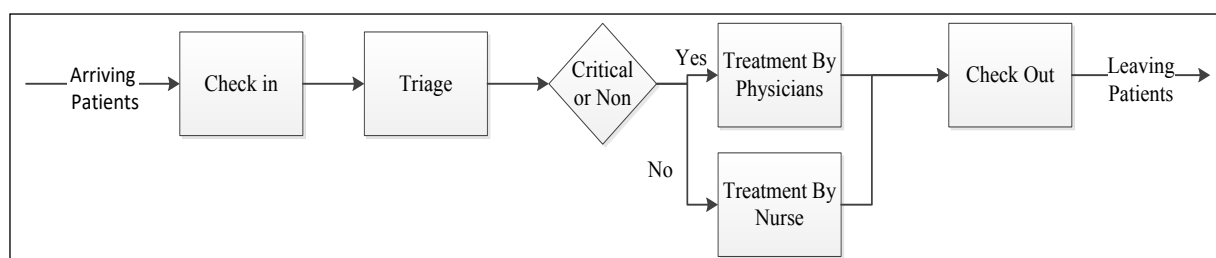


Figure 23: Patient Flow

The patient flow situation in the hospital is as follows: the patient arriving at the hospital is registered first. The registered patient is treated by the nurse in triage section for preliminary diagnosis. Depending on the urgency of the patient, they can either contact the doctor immediately or the patient waits according to the availability of the doctor. Once the doctor has treated the patient, the patient checks out and leaves the hospital. Figure 24 shows the patient flow diagram in detail.

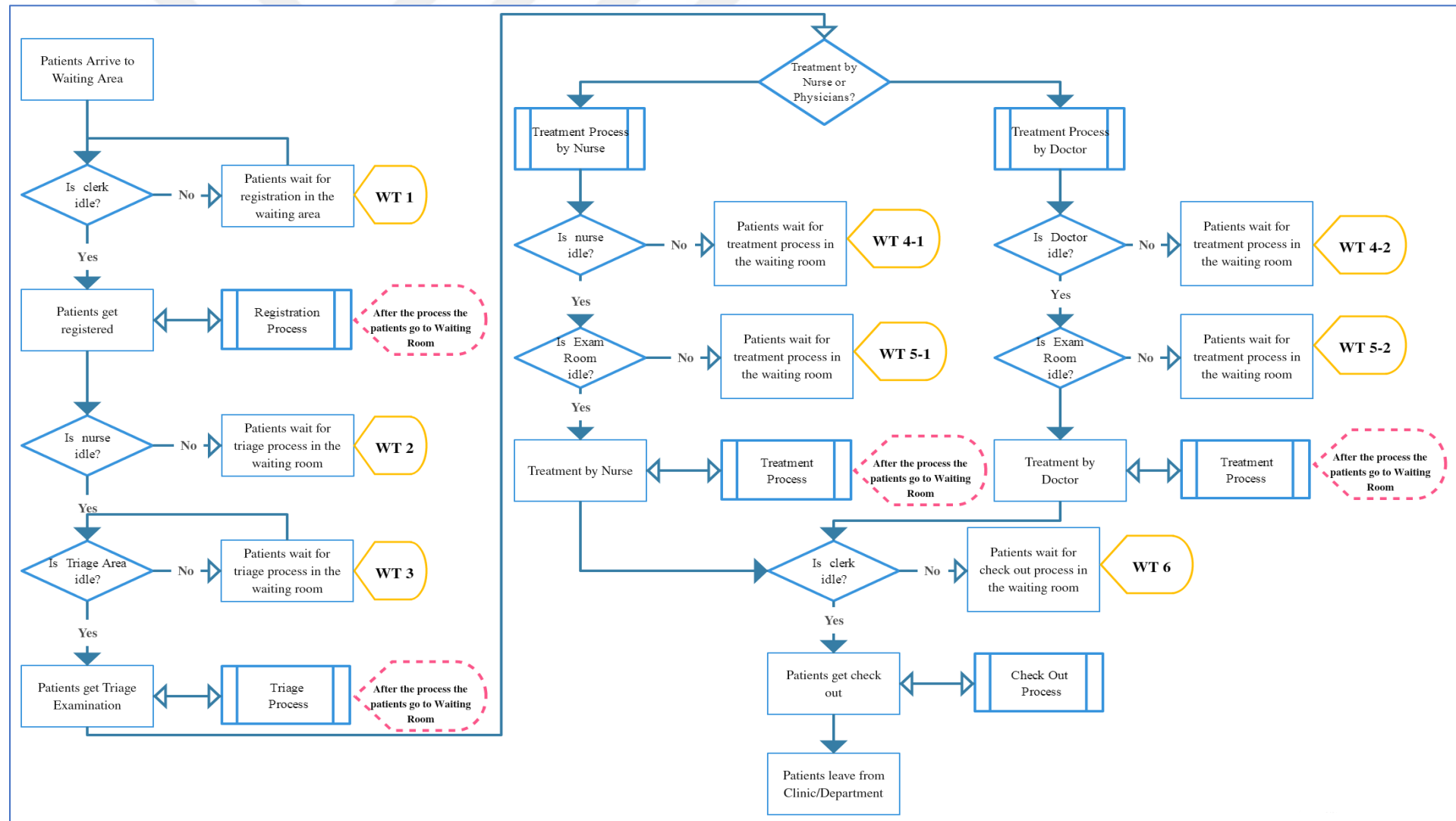


Figure 24: The Flowchart of the Patient Flow in the Emergency Department

General, the averages were used to compute a distribution exhibiting of the number of people who arrived to hospital. Due to the nature of this portion of information, it was not as authoritative to contract data beyond the average. Using means from the various sources, an average patient entrance rate, number of resources was decided upon. The other activity distributions derived from the data collected from reports. The processes necessitated distributions that were generated from the data in Table 25.

Table 25: Simulation Process Time

Process	Time Assigned	Min Value	Mean Value	Max Value
Arriving Patient	Triangular (1.0, 10.0, 18.0)	1.0	10.0	18.0
Check-in	Beta (2.0, 5.0, 7.0)	2.0	5.0	7.0
Triage	Exponential (0.0, 12.0, 0)	---	12.0	---
Treatment by Physician	Uniform (9.0, 17.0, 23.0)	9.0	17.0	23.0
Treatment by Nurse	Weibull (18.0, 32.0, 0.0)	18.0	---	32.0
Check-out	Uniform (2.0, 4.0, 5.0)	2.0	4.0	5.0

Data evaluation software (Expert fit Analyzer in Flexsim HC) was used to analyze the raw data verified in the resources. Each of the time periods registered above are procedures that some patient requirements to go through while they are in the hospital. Each of these routes proceeds an average amount of time, with a certain distribution. Using data analysis software accurately simulated the various processes that occur when a patient goes to a clinic.



Figure 25: Simulation Model Screen View 1

When the model runs, the result data thoroughly match the actual real data that is collected. This is the fundamental model and is being used to demonstrate the great potential of modeling software being used in the experimental throughput analysis (see Figure 25 and Figure 26).



Figure 26: Simulation Model Screen View 2

The computer simulation model has worked properly according to the gathered data. In order to make the simulation run even better, it will be necessary to collect more data from researches and update the model based on the scenarios. Because of the differences between researches, it is important to collect data wherever possible for a simulation model to correctly represent the clinic that is looking to implement variations.

The preconditions limitations of the simulation model;

- * No division of work shifts of resources of the clinic or ED (no needed resources scheduling),
- * A 24-hour healthcare service period,
- * Patients have two options to get treated by physicians or nurses (after the treatment process, the patients leave from the clinic or registered for the polyclinic),
- * After every process, the patients go to waiting room to wait the next process (otherwise,

there will be queues where there are transactions, and the next patient will not benefit from the process),

- * The same resources may have different process times for patients (distribution of process time),
- * Same resources can do two different things at different times (such as check-in and check-out),
- * The system works with the principle that the first come-first treatment (FIFO~FIFT).



2.3. Design of Experiment Structure

2.3.1. Overview of Design of Experiment

The idea of experiment design was first presented by Dr. Fisher in 1935. Fisher wrote a book related to statistical methods for use in laboratory studies for researchers. However, new methods such as statistical variance analysis have been found to be related to experimental design. Fisher then wrote his first print on experiment design in 1935. The last edition was published in 1971 by Hafner Publishing as Reprinted by Arrangement (R. A. Fisher, 1971).

DOE has been used especially in laboratory studies when it is a statistical method. The use of this method is expanding over time. The DOE related literature review is shown in Table 26.

DOE is generally an effective statistical method used to improve process performance or product quality. The DOE consists of four steps. These are: are: planning, designing, conducting, analyzing (Antony, 2003). By applying these steps with obtaining accurate data in the DOE, it is ensured that a process performance or quality of a product are supplied. However, there are different factors in producing each product and different levels for each factor. In such cases, different methods within the DOE are applied.

Multi-objective complications comprise many restrictions may not able to answered itself inadequate DOE beside computer simulations (Mavris, Bandte, & DeLaurentis, 1999). Experimental design approach and computer simulation technique are identified to assess the effects of the constraints and its interfaces particularized in the process. The factors triggered the effects created by the interaction of the factors. On the other hand, these factors produced the responses value.

DOE involves a set of mathematical and statistical methods expended in the development of an acceptable functional affiliation between a response of relevance, y , and a number of linked control (or input) variables symbolized by $x_1, x_2, \dots, x_k$ or $A, B, \dots, N$ (Khuri & Mukhopadhyay, 2010). The essential idea is to appropriate a model for the response variable and then investigate various settings of interest for the descriptive variables (Ding et al., 2004).

Table 26: Literature Review: Fields of DOE Applied

Literature/Field	Research Topics	Author(s)- Year
Literature-Book	The Design of Experiment (Published in 1935,1937, 1942, 1947, 1949, 1951, 1953, 1960, 1966)	(R. A. Fisher, 1971)
Literature-Book	The Design and Analysis of Experiments	(Kempthorne, 1952)
Literature-Book	Introduction to Quality Engineering: Designing Quality into Products and Processes	(Taguchi, 1986)
Healthcare	Orthopedic clinical research. Deficiencies in experimental design and determinations of outcome	(Gartland, 1988)
Literature-Book	Fundamental concepts in the Design of Experiments (Published in 1964,1973, 1982, 1999)	(Hicks & Turner, 1999)
Healthcare	Healthcare simulation modeling and optimization using Med Model	(Price & Harrell, 1999)
Literature-Book	Design of Experiments, Principles and Applications	(Eriksson, Johansson, Kettaneh-Wold, Wikström, & Wold, 2001)
Literature-Book	Design of Experiments for Engineers and Scientists	(Antony, 2003)
Literature-Book	Reliability Improvement with Design of Experiment	(Condra, 2001)
Manufacturing	Design and experiment of a 3-DOF parallel micro mechanism utilizing flexure hinges	(Yi, Chung, Na, Kim, & Suh, 2003)
Healthcare	Designing simulation experiments with controllable and uncontrollable factors for applications in healthcare	(Dehlendorff, Kulahci, & Andersen, 2010)
Manufacturing	Quality Improvement in a Manufacturing Company Using Design of Experiment (DOE)	(Chiong, Mamat, & Eng, 2011)
Literature-Book	Design and Analysis of Experiments	(Montgomery, 2012)
Healthcare	Design of Experiment (DOE) Case Studies in Healthcare	(Aslan, 2015)
Food	Design of Experiments for Food Engineering	(Pedersen, 2015)
Natural Science	Applied Statistical Design of Experiments: Applications in Natural Sciences	(Rauf, 2015)
Healthcare	Emergency department logistic optimization using design of experiments: From triage to high quality of service	(Vazquez-Ibarra, Medina-Ramirez, & Jimenez-Saucedo, 2016)
Energy	Identifying main factors of capacity fading in lithium ion cells using orthogonal design of experiments	(Su et al., 2016)
Healthcare	Combined semi-empirical screening and design of experiments (DOE) approach to identify candidate formulations of a lyophilized live attenuated tetravalent viral vaccine candidate	(Patel et al., 2017)
Environment	Combined Homogeneous Surface Diffusion Model? Design of experiments approach to optimize dye adsorption considering both equilibrium and kinetic aspects	(Muthukkumaran & Aravamudan, 2017)

DOE usually includes the first-order (see equation 42, (Oehlert, 2010)) and the multiple linear equation (see equation 43 with two factors) equations. On the basis of these equations, the response values obtained from the factors are revealed. If there is no interaction between the factors, the first-order equation is obtained. With the interaction between the factors, the multiple linear equations occur at the first-order. Optimization models of the multiple linear equations are more difficult to solve. The purpose of multiple regression is to use simultaneous use of a set of predictive variables (Hoyt, Leierer, & Millington, 2014). In this research, both the existence of linear and multiple linear equations and the fact that the decision variables included in the optimization model are integers make the solution of the problem more complex.

$$y_{ij} = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \dots + \beta_q x_{qi} + \varepsilon_{ij} \quad (42)$$

$$y_{ij} = \beta + \beta_1 x_1 + \beta_2 x_2 + \beta_3 (x_1 x_2) + \varepsilon_{ij} \quad (43)$$

where β_i is regression coefficient, x_i and x_{ij} are factors, ε_{ij} is random error and β is a qxq matrix (Oehlert, 2010).

Factors in multiple interaction linear equations are not considered. However, the mathematical equation that becomes formed when the levels of factors in the experiment design participate in the calculus becomes more complex. Until now, the mathematical equation with multiple interaction experiment design has not been obtained in any research. For the first time in this research, the multiple interaction full factorial mathematical equations 44, 45, 46, 47, and 48 with two factors with two levels are formulated as follows in this research.

$$y_1 = c + c_1 x_i + c_2 x_j + c_{12} (x_i x_j) + \varepsilon_{ij} \quad (44)$$

$$y_2 = c_a x_{il} x_{j1} + c_b x_{il} x_{j2} \quad (45)$$

$$y_3 = c_c x_{il} x_{j1} + c_d x_{il} x_{j2} \quad (46)$$

and;

$$i \neq j \quad (47)$$

$$y = y_1 + y_2 + y_3 \quad (48)$$

Where;

- y : Total response
- y_1 : Response of multiple linear equation
- y_2 : Response of 1st level of factor i
- y_3 : Response of 2nd level of factor i
- c : The first coefficient
- c_1 : The second multiplier coefficient
- c_2 : The third multiplier coefficient
- x_i : The factor i
- x_j : The factor j
- c_a and c_b : The first multiplier in level 1 of factor i
- c_c and c_d : The second multiplier in level 1 of factor i
- c_{il} : l^{th} level of factor i
- c_{j1} : The first multiplier in level 1 of factor j
- c_{j2} : The first multiplier in level 2 of factor j

For an equation 49 with more than two factors, it is expressed as:

$$y = c + \sum [c_i x_i + c_{12}(x_i x_j) + c_{i1} x_{il} x_{j1} + c_{i2} x_{il} x_{j2} + \dots + c_{in} x_{il} x_{jn} + \varepsilon_{ij}] \quad (49)$$

2.3.2. Types of Design of Experiment

When DOE varieties are examined, Full Factorials, Fractional Factorials, Screening Experiments, Response Surface Analysis, EVOP (evolutionary operations) and Mixture Experiments are available. In this chapter, full factorial design multi-level method is used because each factor has different levels.

2.3.2.1. Full Factorial Design

It is the most used method in the experiment design technique. In this method, the combination of all the factors that influence the response variable is taken into account. factors are usually considered as 2 levels. How many combinations are formed is calculated with 2^k . The combination of factors in different levels is discussed in multi-level factorial design.

2.3.2.2. Fractional Factorial Design

Fractional factorial design is a method that allows less experimentation (in terms of time and cost) to be difficult to perform. In this method, 2 levels are used for the factors. The combination of these factors is calculated by the 2^{k-p} formula, where each factor has 2 levels, there are k factors, and $1/2^p$ fraction of the number of possible factor level combinations.

2.3.2.3. Multi-Level Factorial Design

It is an experimental design that takes into account the different levels of factors that will affect the response function. In this part of the thesis, experimental design was made using multi-level factorial level design. The multiplicity of scenario diversity in simulation studies provides the basis for the use of multi-level factorial experiments (Dziak, Nahum-Shani, & Collins, 2012). In this study, which has two different response functions, two of the five different factors were considered as 2 levels and 3 factors as 3 levels. Details are given in Section 2.3.3.

2.3.2.4. Screening Experiments

The Screening Design method determines which of the factors to be used in the experiment affects the response function. In this experiment, the factors are trying to find the main factors which are very influential on the effect of the interaction (Handbook, 2012). For this reason, this method allows the effects of these factors to be explored by determining the number of efficient factors. This method is also economical as a fractional factorial design approach.

2.3.2.5. Response Surface Analysis

Response Surface Analysis (RSM) is an optimization tool. Optimization is done to identify the best set of levels of factors in an experiment in which factors and levels are evident. Another definition of RSM is to create an empirical model using mathematical and statistical techniques. In short, it is a mathematical and statistical method that is used both to answer the effect of the factors present in the experiment on the response function and to calculate the optimum values of the levels of these factors. When applying this method, it gives you the ability to determine how the response function affects the surface. This method is used more as a quality tool (Atalan, 2014). RSM is also studied in two different ways. These are Central Composite Design (CCD) and Box-Behnken Designs (BBD).

2.3.2.5.1. Box-Behnken Designs

Box-Behnken designs allow for gaining efficient estimation of the first-order and second-order coefficients. Because Box-Behnken designs often have fewer design points, they can be less expensive to do than CCDs with the same number of factors. However, because they do not have an embedded factorial design, they are not suited for sequential experiments.

2.3.2.5.2. Central Composite Design

Central Composite Design (CCD) is one of the RSM tools. Generally, CCD focuses on fitting a second-order, linear regression model of the mean responses and the levels of the design variables (as a strong suggestion of the CCD to the simulation analyst interested in performing designed second-order simulation experiment). The previous studies have been on maximizing or minimizing the mean of the responses (Ding et al., 2004). This method states that the variability of responses is stable, however, this idea was not able to work in real problems (Atalan, 2014).

2.3.2.6. Evolutionary Operations

The Evolutionary Operations (EVOP) method allows minor changes to the levels of the factors to be used in the experiment (Raymond H. Myers Douglas C. Montgomery, 2016). These changes are so small that they do not affect the response function in experiments for a product or service. This method is already used for 2-level factors.

2.3.2.7. Mixture Experiments

Mixture Experiments method used as a measurement of the effects on the response alone or as a result of the interactions of the factors to be used in the experiment. The empirical estimates of the responses given for the combination of experiments to be generated by considering the levels of the factors and factors of the experiment are to be tested.

2.3.3. Establishment of Design of Experiment for the Application

The experiment is a full factorial multi-level design that has five experimental variables: physicians A, nurses B, clerks C, triage rooms D, and exam rooms E, and each factor has different level with two replicated on each design combination. The experimental conditions are displayed in Table 27.

Table 27: Conditions of the Experiment

Factors	Level 1	Level 2	Level 3
A: Number of Physicians	1.00	2.00	3.00
B: Number of Nurses	1.00	2.00	3.00
C: Number of Clerks	1.00	2.00	***
D: Number of Triage Rooms	1.00	2.00	***
E: Number of Exam Rooms	1.00	2.00	3.00

Using design of experiment module in Minitab computer software which is acceptable application in academic area provides level of factors, replicate and how many times the experiment run automatically and easily. Table 28 that shows the factors' levels with total runs. Furthermore, this application supplies the needed statistical output and gives detail results for facilities.

Table 28: Design of Experiment Full/Multi Level Factorial Design

Design of Experiment Structure	
Factors	5.00
Number of Replicates	2.00
Base Runs	108
Total Runs	216

According to DOE, we need to run our experiment in 216 (see Table 29) which is our total scenario for simulation model in a short time. In actual life, it seems impossible to apply this amount of runs presently. If we want to get analysis of variance (ANOVA) output, our model runs at least two times; otherwise, Anova table will not be provided from the experiment.

Table 29: Scenarios Variables

Experiment Variables	Scenario 1	Scenario 2	...	Scenario 216
Number of Physicians	1.00	1.00	...	3.00
Number of Nurses	2.00	3.00	...	3.00
Number of Clerks	2.00	3.00	...	2.00
Number of Triage Rooms	3.00	2.00	...	2.00
Number of Exam Rooms	3.00	2.00	...	3.00

2.3.4. Interpretation of Statistical Results

Each scenario's detail result is provided by the simulation application that shows understanding of the possible performance of the system. Both simulation's and DOE's results demonstrate that controllable factors which are physicians, nurses, exam rooms, triage chairs, and clerks more effectively impact on the clinic's performance. Two types of data have been considered after the simulation and experiment design. This data is calculated considering the information in the scenario. The first results are related to the total number of patients being treated and the second is related to the waiting times of the patients in the hospital (see Table 30). All the data regarding the total number of patients treated and the waiting time of the patients are included in the appendix (see Table 50: Data Obtained in Simulated Multi-Level Factorial Design)

Table 30: Numbers of Treated Patients and Waiting Times

Scenarios	Patient Outputs	Waiting Time
Scenario 1	96.00	15.00 min
Scenario 2	160.00	9.00 min
Scenario 3	65.45	22.00 min
...	...	...
Scenario 152	102.86	14.00 min
Scenario 153	25.71	56.00 min
Scenario 154	41.74	34.50 min
...	...	...
Scenario 214	12.74	113.00 min
Scenario 215	12.20	118.00 min
Scenario 216	10.95	131.50 min

The statistical analysis of the data obtained in simulation is shown in Figure 27 (a) and Figure 27 (c) and Figure 27 (b) and Figure 27 (d) as being suitable for normal distribution. The data obtained by running the simulation model correctly are analyzed by the experimental design method. As a result of these analyzes, it is revealed which factors are more important and which factors are not important.

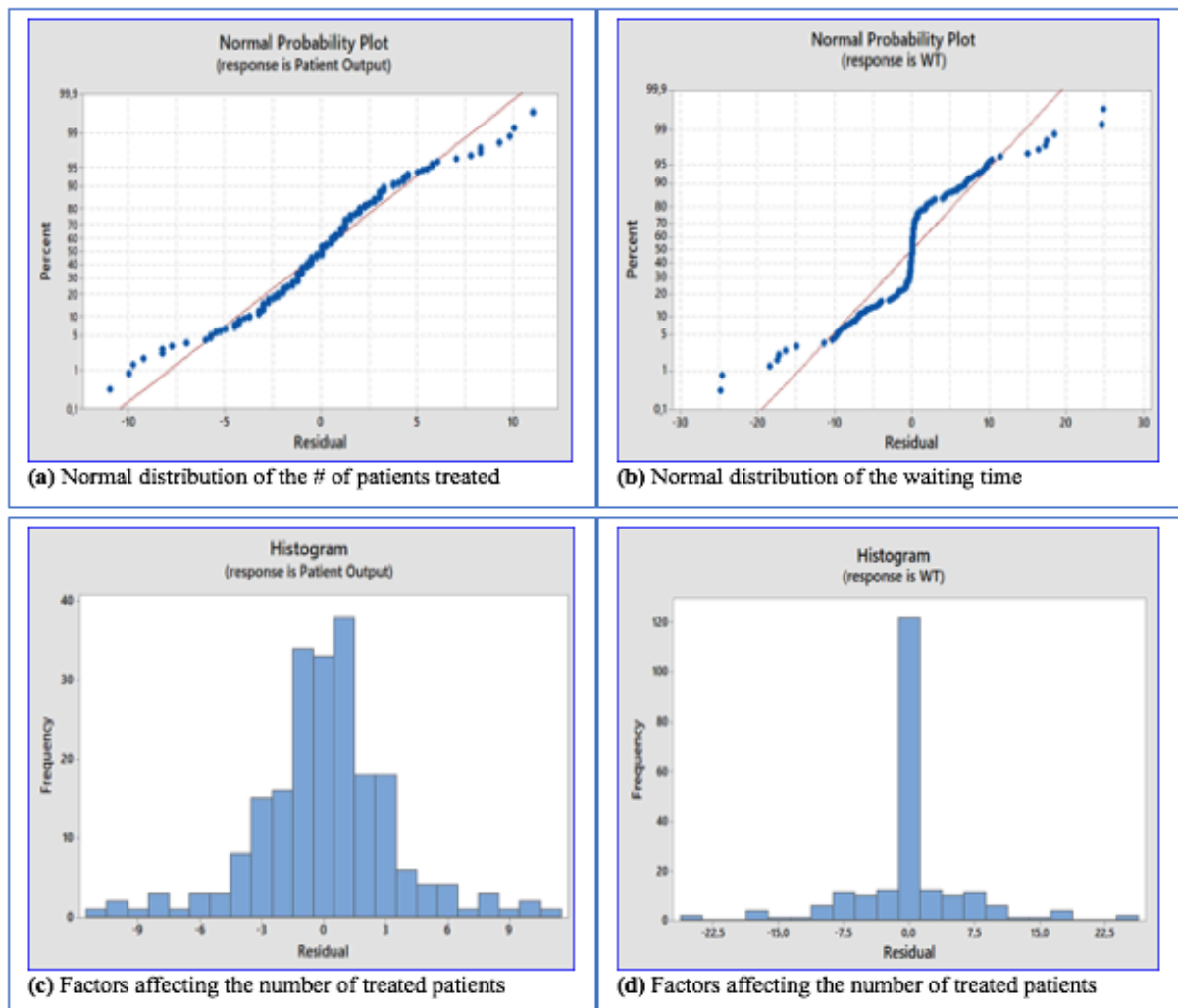


Figure 27: Normal Distribution of Data

- Statistical results of the factors related to the number of patients treated and the total waiting time of the patients in the hospital:

As a result of statistical analysis, the number of doctors, nurses, and exam rooms directly affect the total number of patients treated. In particular, the number of triages appears to have not had much effect on the number of patients treated. However, it is shown in Table 31 and in Figure 28 that these factors influence the number of treated patients at an important level with the interaction. These results are also found to have the same effect on the waiting times that patients are exposed to in the hospital in Table 32 and in Figure 29.

Table 31: Statistical Results of the Factors Related to the Number of Patients Treated

Factors	DF	SS	MS	F-Value	P-Value
Model	107	457645	4277.10	188.59	0.00
Linear	8	286482	35810.2	1578.98	0.00
P	2	159824	79912.2	3523.56	0.00
N	2	95492	47746	2105.26	0.00
C	1	33	33.10	1.46	0.23
ER	2	31111	15555.6	685.89	0.00
T	1	21	21.1	0.93	0.337
2-Way Interactions	25	62000	2480	109.35	0.00
P*N	4	23682	5920.5	261.05	0.00
P*C	2	245	122.4	5.4	0.006
P*ER	4	14490	3622.5	159.73	0.00
P*T	2	1733	866.3	38.2	0.00
N*C	2	587	293.7	12.95	0.00
N*ER	4	3104	776	34.22	0.00
N*T	2	1111	555.6	24.5	0.00
C*ER	2	596	298.1	13.14	0.00
C*T	1	13	13.3	0.58	0.446
ER*T	2	16439	8219.3	362.41	0.00
3-Way Interactions	38	42164	1109.6	48.92	0.00
P*N*C	4	1062	265.4	11.7	0.00
P*N*ER	8	7874	984.3	43.4	0.00
P*N*T	4	2567	641.6	28.29	0.00
P*C*ER	4	4147	1036.7	45.71	0.00
P*C*T	2	910	455.2	20.07	0.00
P*ER*T	4	14040	3510	154.77	0.00
N*C*ER	4	4326	1081.6	47.69	0.00
N*C*T	2	631	315.7	13.92	0.00
N*ER*T	4	4990	1247.4	55.00	0.00
C*ER*T	2	1617	808.5	35.65	0.00
4-Way Interactions	28	59486	2124.5	93.68	0.00
P*N*C*ER	8	2822	352.7	15.55	0.00
P*N*C*T	4	796	199	8.78	0.00
P*N*ER*T	8	44622	5577.8	245.94	0.00
P*C*ER*T	4	7353	1838.1	81.05	0.00
N*C*ER*T	4	3894	973.4	42.92	0.00
5-Way Interactions	8	7513	939.1	41.41	0.00
P*N*C*ER*T	8	7513	939.1	41.41	0.00
Error	108	2449	22.7	***	***
Total	215	460095	***	***	***

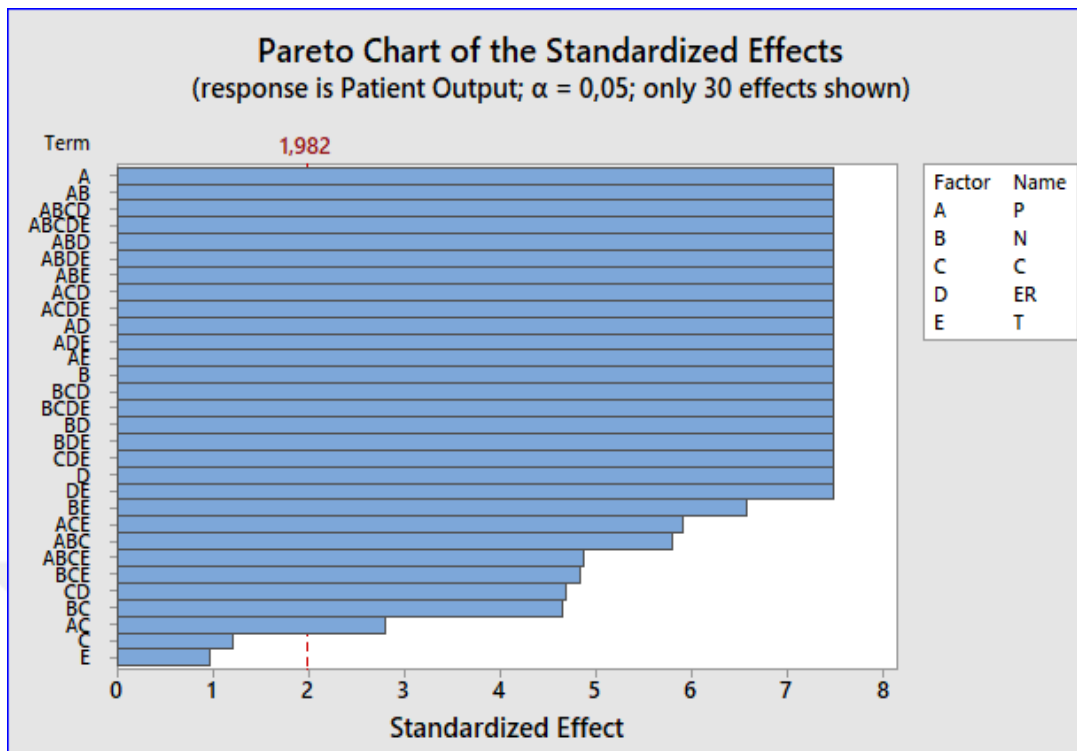


Figure 28: Factors Affecting the Number of Treated Patients

Table 32: Results of the Factors Affecting the Total Waiting Time of the Patients

Factors	DF	SS	MS	F-Value	P-Value
Model	107	234454	2191.2	27.7	0.00
Linear	8	137995	17249.3	218.09	0.00
P	2	35130	17564.8	222.07	0.00
N	2	64791	32395.6	409.58	0.00
C	1	72	72.4	0.92	0.341
ER	2	37818	18909.2	239.07	0.00
T	1	183	183.1	2.31	0.131
2-Way Interactions	25	45882	1835.3	23.2	0.00
P*N	4	1914	478.5	6.05	0.00
P*C	2	111	55.4	0.7	0.499
P*ER	4	14547	3636.7	45.98	0.00
P*T	2	1951	975.7	12.34	0.00
N*C	2	589	294.7	3.73	0.027
N*ER	4	11818	2954.6	37.36	0.00
N*T	2	1016	508.2	6.43	0.002
C*ER	2	1083	541.7	6.85	0.002
C*T	1	14	13.6	0.17	0.679
ER*T	2	12838	6419.1	81.16	0.00
3-Way Interactions	38	26934	708.8	8.96	0.00

P*N*C	4	514	128.6	1.63	0.173
P*N*ER	8	9991	1248.8	15.79	0.00
P*N*T	4	3921	980.3	12.39	0.00
P*C*ER	4	1499	374.8	4.74	0.001
P*C*T	2	654	327.1	4.14	0.019
P*ER*T	4	2920	729.9	9.23	0.00
N*C*ER	4	849	212.3	2.68	0.035
N*C*T	2	846	422.9	5.35	0.006
N*ER*T	4	5529	1382.2	17.47	0.00
C*ER*T	2	211	105.4	1.33	0.268
4-Way Interactions	28	20732	740.4	9.36	0.00
P*N*C*ER	8	686	85.7	1.08	0.38
P*N*C*T	4	198	49.4	0.62	0.646
P*N*ER*T	8	16603	2075.4	26.24	0.00
P*C*ER*T	4	431	107.7	1.36	0.252
N*C*ER*T	4	2815	703.7	8.9	0.00
5-Way Interactions	8	2911	363.8	4.6	0.00
P*N*C*ER*T	8	2911	363.8	4.6	0.00
Error	108	8542	79.1	***	***
Total	215	242996	***	***	***

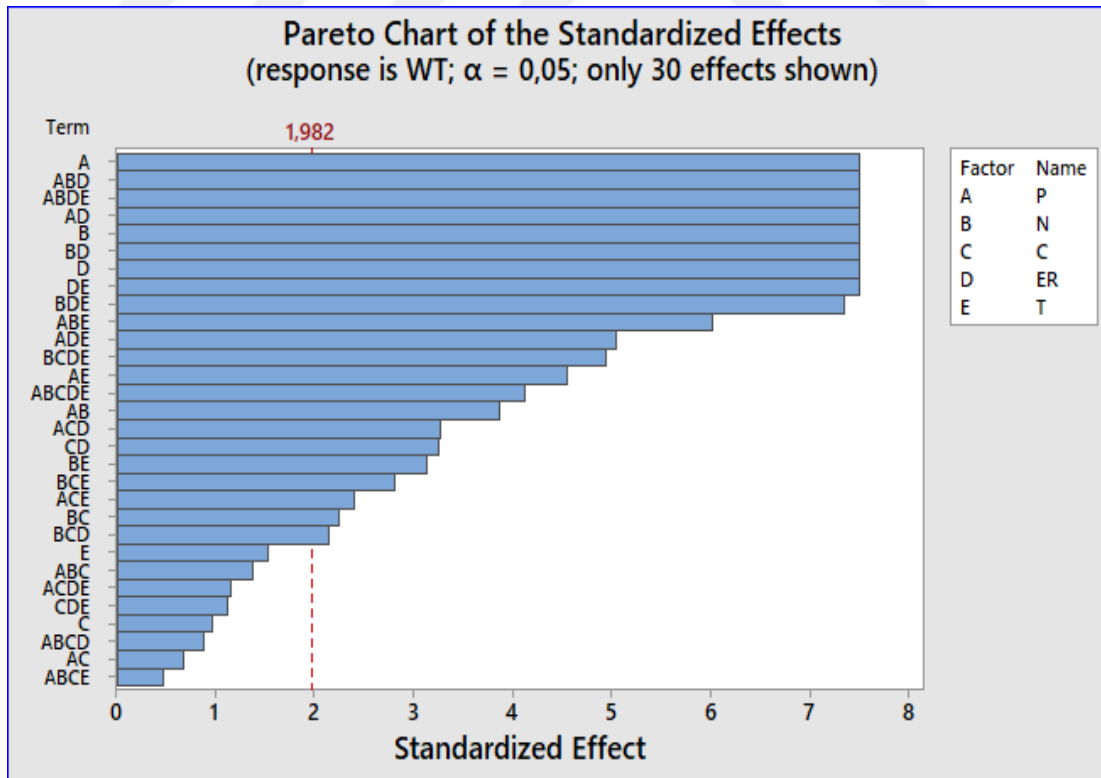


Figure 29: Factors Affecting the Total Waiting Time of the Patient

Summary of statistical results of the input variables of healthcare services is explained in

Table 33. According to this table, the effect of the input variables on the outputs without interacting and interacting with each other is shown.

Table 33: Summary of Statistical Results of the Input Variables

Input Variables	Status*	The Number of Patients Treated			Waiting Time of the Patients		
		F-Value	P-Value	Status**	F-Value	P-Value	Status**
P	Individual	3523.56	0.001	Sig (p<0.05)	222.07	0.002	Sig (p<0.05)
N		2105.26	0.001	Sig (p<0.05)	409.58	0.001	Sig (p<0.05)
C		1.46	0.230	Not Sig	0.92	0.341	Not Sig
ER		685.89	0.001	Sig (p<0.05)	239.07	0.001	Sig (p<0.05)
T		0.93	0.337	Not Sig	2.31	0.131	Not Sig
P*N	2-Way Interactions	261.05	0.001	Sig (p<0.05)	6.05	0.001	Sig (p<0.05)
P*C		5.40	0.060***	Provisionally Sig	0.70	0.499	Not Sig
P*ER		159.73	0.001	Sig (p<0.05)	45.98	0.001	Sig (p<0.05)
P*T		38.20	0.001	Sig (p<0.05)	12.34	0.001	Sig (p<0.05)
N*C		12.95	0.001	Sig (p<0.05)	3.73	0.027	Sig (p<0.05)
N*ER		34.22	0.001	Sig (p<0.05)	37.36	0.001	Sig (p<0.05)
N*T		24.50	0.001	Sig (p<0.05)	6.43	0.002	Sig (p<0.05)
C*ER		13.14	0.001	Sig (p<0.05)	6.85	0.002	Sig (p<0.05)
C*T		0.58	0.446	Not Sig	0.17	0.679	Not Sig
ER*T		362.41	0.001	Sig (p<0.05)	81.16	0.001	Sig (p<0.05)
P*N*C	3-Way Interactions	11.70	0.001	Sig (p<0.05)	1.63	0.173	Not Sig
P*N*ER		43.40	0.001	Sig (p<0.05)	15.79	0.001	Sig (p<0.05)
P*N*T		28.29	0.001	Sig (p<0.05)	12.39	0.001	Sig (p<0.05)
P*C*ER		45.71	0.001	Sig (p<0.05)	4.74	0.001	Sig (p<0.05)
P*C*T		20.07	0.001	Sig (p<0.05)	4.14	0.019	Sig (p<0.05)
P*ER*T		154.77	0.001	Sig (p<0.05)	9.23	0.001	Sig (p<0.05)
N*C*ER		47.69	0.000	Sig (p<0.05)	2.68	0.035	Sig (p<0.05)
N*C*T		13.92	0.000	Sig (p<0.05)	5.35	0.006	Sig (p<0.05)
N*ER*T		55.00	0.002	Sig (p<0.05)	17.47	0.001	Sig (p<0.05)
C*ER*T		35.65	0.001	Sig (p<0.05)	1.33	0.268	Not Sig
P*N*C*ER	4-Way Interactions	15.55	0.000	Sig (p<0.05)	1.08	0.380	Not Sig
P*N*C*T		8.78	0.001	Sig (p<0.05)	0.62	0.0646***	Provisionally Sig
P*N*ER*T		245.94	0.000	Sig (p<0.05)	26.24	0.001	Sig (p<0.05)
P*C*ER*T		81.05	0.001	Sig (p<0.05)	1.36	0.252	Not Sig
N*C*ER*T		42.92	0.002	Sig (p<0.05)	8.90	0.001	Sig (p<0.05)
P*N*C*ER*T	5-Way Interactions	41.41	0.002	Sig (p<0.05)	4.60	0.001	Sig (p<0.05)

2.4. Optimization Models of the Research

2.4.1. Establishment of Optimization Models for the Application

In the direction of the data obtained in simulation and experiment design, optimization can be defined as finding the best decision variable among all possibilities (Carson & Maria, 1997). The goal of simulation optimization is to minimize the resources spent by maximizing or minimizing the objective function in the direction of information obtained with the help of a simulation model (Carson & Maria, 1997). The notations of the healthcare system are presented in Table 34.

Table 34: Notations of the Healthcare System

<i>Parameters</i>	<i>Descriptions (depend on scenarios)</i>
c_1, c_2	Clerk 1 and Clerk 2
n_1, n_2, n_3	Nurse 1, Nurse 2, and Nurse 3
p_1, p_2, p_3	Physician 1, Physician 2, and Physician 3
e_1, e_2, e_3	Exam Room 1, Exam Room 2, and Exam Room 3
t_1, t_2	Triage 1 and Triage 2
t_{c1}, t_{c2}	The time required for the patient to wait until clerks are idle
$t_{n1}, t_{n2}, t_{n3}, t_{n4}, t_{n5}, t_{n6}$	The time required for the patient to wait until nurses are idle
$t_{p1}, t_{p2}, t_{p3}, t_{p4}, t_{p5}, t_{p6}$	The time required for the patient to wait until physicians are idle
$t_{e1}, t_{e2}, t_{e3}, t_{e4}, t_{e5}, t_{e6}$	The time required for the patient to wait until exam rooms are idle
d_d	The doctor is assigned to exam the patient, nurse is idle
d_n	The nurse is assigned to exam the patient, doctor is idle
Z^s_{po}	The total number of the treated patient is based on scenario s
Z^s_t	The total treatment time of the patient is based on scenario s
Z^s_{wt}	The average waiting time of the patient is based on scenario s
Z^s_{los}	The average length of stay of the patient is based on scenario s
W_p	The patient's waiting time for physicians
W_n	The patient's waiting time for nurses
W_e	The patient's waiting time for exam rooms
W_c	The patient's waiting time for clerks
W_{tr}	The patient's waiting time for triage chairs
p	The maximum number of physicians

n	<i>The maximum number of nurses</i>
e	<i>The maximum number of exam rooms</i>
t	<i>The maximum number of triage areas</i>
c	<i>The maximum number of clerks</i>
Decision Variables	Definitions
x_c	<i>The numbers of clerks are busy or idle</i>
x_n	<i>The numbers of nurses are busy or idle</i>
x_p	<i>The numbers of physicians are busy or idle</i>
x_e	<i>The numbers of exam rooms are busy or idle</i>
x_t	<i>The numbers of triages are busy or idle</i>

According to this numeric research, as a result of analysis two optimization models have emerged. These models consist of the number of patients treated and the total waiting time for patients to be treated in the hospital. In the first model (see 57), the optimization model ensures that the total number of treated patients is maximized. The second model (see equation 60) aims to reduce the total waiting time of the patients to the minimum level during treatment.

▪ **Optimization models of total treated patients:**

$$\text{Max } [Z_{po}^s] = f\{x_p, x_n, x_c, x_t, x_e\} \quad (57)$$

subject to

$$\text{Number of Physicians} \leq b_i$$

$$\text{Number of Nurses} \leq b_i$$

$$\text{Number of Clerks} \leq k_i$$

$$\text{Number of Triage Rooms} \leq k_i$$

$$\text{Number of Exam Rooms} \leq b_i$$

where; b_i the number of resources of type 1 ($i = 1, 2, 3$), and k_j the number of resources of type 2 ($i = 1, 2$).

▪ **Notations and optimization model of patients' waiting time in hospital:**

- The waiting time for physicians; W_p ,
- The waiting time for nurses; W_n ,

- The waiting time for exam rooms; W_e ,
- The waiting time for clerks; W_c ,
- The waiting time for triage; W_{tr} ,

$$Z^s_{wt} = W_p + W_n + W_e + W_c + W_{tr} \quad (58)$$

$$Total\ Waiting\ Time = Min\ Z^s_{wt} \quad (59)$$

Subject to

$$Number\ of\ Physicians\ (x_p) \leq p$$

$$Number\ of\ Nurses\ (x_n) \leq n$$

$$Number\ of\ Clerks\ (x_c) \leq c$$

$$Number\ of\ Triage\ Rooms\ (x_t) \leq t$$

$$Number\ of\ Exam\ Rooms\ (x_e) \leq e$$

2.4.2. Mathematical Expansion of Objective Functions

In the two different optimization models were created and 108 scenarios were generated with the help of DOE. As a result of these scenarios, the best results are obtained. However, since such problems are stochastic, they are expressed only by closed formulas (Equations 57 and 59). In order to form these equations, some constraints of the systems must be determined in advance.

There are 262,144 scenarios of the optimization equation created to obtain the objective functions. First, the steps of the simulation model with different states are explained in table A.3. When examining the optimization models, it should be considered as 4 stages. The first stage is to maximize the number of patients treated, n . In the second stage, it is aimed to minimize the time of patient treatment, t_t . In the third stage, patients are aiming to keep their waiting time, w_t at a moderate level. The fourth stage is related to the sum of the results obtained in the second stage and the third stage. That is, the total time the patient spent, t_{LOS} in the hospital is minimized.

2.4.2.1. Total Number of Patients Who Are Treated in This System

$$\text{Max } Z_{PO} = n$$

2.4.2.2. Average Treatment Time in this System

* Step 1: Check-in Process:

$$t_{c1} + t_{c2} + (t_{c1} + t_{c2}) = 2 \sum_{h=1}^2 t_{ch}$$

* Step 2₁: Triage Process:

$$t_{n1} + t_{n2} + t_{n3} + t_{n4} + t_{n5} + t_{n6}$$

$$(t_{n1} + t_{n2} + t_{n3} + t_{n4} + t_{n5} + t_{n6}) = 2 \sum_{k=1}^6 t_{ck}$$

* Step 2₂: Triage Process in the Triage Area:

$$\begin{aligned} & \min\{t_{n1}, t_{n2}, t_{n3}\} + \min\{t_{n1}, t_{n2}, t_{n3}\} + \\ & \min\{(t_{n1}, t_{n2}), (t_{n1}, t_{n3}), (t_{n2}, t_{n3})\} = \\ & \min\{(t_{n1}, t_{n2}), (t_{n1}, t_{n3}), (t_{n2}, t_{n3})\} + \end{aligned}$$

$$2 \sum_{l=1}^2 \min\{t_{n1}, t_{n2}, t_{n3}\}$$

* Step 3₁: Treatment Process by Physicians:

$$(t_{p1} + t_{p2} + t_{p3} + t_{p4} + t_{p5} + t_{p6}) +$$

$$(t_{p1} + t_{p2} + t_{p3} + t_{p4} + t_{p5} + t_{p6}) = 2 \sum_{k=1}^6 t_{pk}$$

* Step 3₂: Treatment Process by Nurses:

$$(t_{n1} + t_{n2} + t_{n3} + t_{n4} + t_{n5} + t_{n6}) +$$

$$(t_{n1} + t_{n2} + t_{n3} + t_{n4} + t_{n5} + t_{n6}) = 2 \sum_{k=1}^6 t_{ck}$$

* Step 3₃: Treatment Process in the Exam Rooms:

$$\min\{t_{n1}, t_{n2}, t_{n3}, t_{p1}, t_{p2}, t_{p3}\} + \min\{t_{n1}, t_{n2}, t_{n3}, t_{p1}, t_{p2}, t_{p3}\} +$$

$$\min\{t_{n1}, t_{n2}, t_{n3}, t_{p1}, t_{p2}, t_{p3}\}$$

Scenario 3₃:5

$$\min \{(t_{n1}, t_{n2}), (t_{n1}, t_{n3}), (t_{n2}, t_{n3}),$$

$$(t_{p1}, t_{p2}), (t_{p1}, t_{p3}), (t_{p2}, t_{p3}), (t_{p1}, t_{n1}), (t_{p1}, t_{n2}), (t_{p1}, t_{n3})$$

$$(t_{p2}, t_{n1}), (t_{p2}, t_{n2}), (t_{p2}, t_{n3}), (t_{p3}, t_{n3}), (t_{p3}, t_{n2}), (t_{p3}, t_{n3})\}$$

Scenario 3₃:6

$$\min \{(t_{n1}, t_{n2}), (t_{n1}, t_{n3}), (t_{n2}, t_{n3}),$$

$$(t_{p1}, t_{p2}), (t_{p1}, t_{p3}), (t_{p2}, t_{p3}), (t_{p1}, t_{n1}), (t_{p1}, t_{n2}), (t_{p1}, t_{n3})$$

$$(t_{p2}, t_{n1}), (t_{p2}, t_{n2}), (t_{p2}, t_{n3}), (t_{p3}, t_{n3}), (t_{p3}, t_{n2}), (t_{p3}, t_{n3})\}$$

Scenario 3₃:7

$$\min \{(t_{n1}, t_{n2}), (t_{n1}, t_{n3}), (t_{n2}, t_{n3}),$$

$$(t_{p1}, t_{p2}), (t_{p1}, t_{p3}), (t_{p2}, t_{p3}), (t_{p1}, t_{n1}), (t_{p1}, t_{n2}), (t_{p1}, t_{n3})$$

$$(t_{p2}, t_{n1}), (t_{p2}, t_{n2}), (t_{p2}, t_{n3}), (t_{p3}, t_{n3}), (t_{p3}, t_{n2}), (t_{p3}, t_{n3})\}$$

Scenario 3₃:8

$$\min\{(t_{p1}, t_{p2}, t_{p3}), (t_{p1}, t_{p2}, t_{n1}), (t_{p1}, t_{p2}, t_{n2}), (t_{p1}, t_{p2}, t_{n3}),$$

$$(t_{p1}, t_{p3}, t_{n1}), (t_{p1}, t_{p3}, t_{n2}), (t_{p1}, t_{p3}, t_{n3}),$$

$$(t_{p2}, t_{p3}, t_{n1}), (t_{p2}, t_{p3}, t_{n2}), (t_{p2}, t_{p3}, t_{n3}),$$

$$(t_{n1}, t_{n2}, t_{n3}), (t_{n1}, t_{n2}, t_{p1}), (t_{n1}, t_{n2}, t_{p2}), (t_{n1}, t_{n2}, t_{p3}),$$

$$(t_{n1}, t_{n3}, t_{p1}), (t_{n1}, t_{n3}, t_{p2}), (t_{n1}, t_{n3}, t_{p3}),$$

$$(t_{n2}, t_{n3}, t_{p1}), (t_{n2}, t_{n3}, t_{p2}), (t_{n2}, t_{n3}, t_{p3})\}$$

* Step 4: Check-out Process:

$$t_{c1} + t_{c2} + (t_{c1} + t_{c2}) = 2 \sum_{h=1}^2 t_{ch}$$

The 4-stage system has different patient treatment times for each stage. In the sum of these, the objective function is generated by minimizing the total patient treatment time.

$$MinZ_{t_t} = 2 \sum_{h=1}^2 t_{ch} + 2 \sum_{k=1}^2 t_{ck} +$$

$$\min\{(t_{n1}, t_{n2}), (t_{n1}, t_{n3}), (t_{n2}, t_{n3})\} +$$

$$2 \sum_{l=1}^2 \min\{t_{n1}, t_{n2}, t_{n3}\} =$$

$$2 \sum_{k=1}^2 t_{pk} + \text{scenario } 3_{123} + 2 \sum_{h=1}^2 t_{ch}$$

Generated optimization model is usually expressed as closed functions because it has a stochastic structure. On average, the total treatment time of the patient is based on the mathematical equation as:

$$Min Z^s_{t_t} = \sum_1^n \frac{[d_d(t^1_{cj} + t^2_{cj} + t^1_{nj} + t_{pj}) + d_n(t^1_{cj} + t^2_{cj} + t^1_{nj} + t_{nj})]}{n}$$

where s indicates the scenario in which the patient was treated. d_1 and d_2 are defined as binary variables and with these variables it will be decided that the patient will be treated by the doctor or by the nurse as below;

$$d_d + d_n = 1$$

$$d_d = \begin{cases} 1, & \text{the doctor is assigned to exam the patient, the nurse is idle} \\ 0, & \text{the nurse is assigned to exam the patient, the doctor is idle} \end{cases}$$

$$d_n = \begin{cases} 1, & \text{the nurse is assigned to exam the patient, the doctor is idle} \\ 0, & \text{the doctor is assigned to exam the patient, the nurse is idle} \end{cases}$$

2.4.2.3. Average Waiting Time in this System

* Step 1: Waiting Time for Check-in Process:

$$\min\{t_{c1}, t_{c2}\}$$

* Step 2₁: Waiting Time for Triage Process:

$$\min\{(t_{n1}, t_{n2}), (t_{n1}, t_{n3}), (t_{n2}, t_{n3})\}$$

* Step 2₂: Waiting Time for Triage Process in the Triage Area:

$$\min\{(t_{n1}, t_{n2}), (t_{n1}, t_{n3}), (t_{n2}, t_{n3})\}$$

* Step 3₁: Waiting Time for Treatment Process by Physicians:

$$\min\{(t_{p1}, t_{p2}, t_{p3})\}$$

* Step 3₂: Waiting Time for Treatment Process by Nurses:

$$\min\{(t_{n1}, t_{n2}, t_{n3})\}$$

* Step 3₃: Waiting Time for Treatment Process in the Exam Rooms:

$$\min\{(t_{n1}, t_{n2}, t_{n3}, t_{p1}, t_{p2}, t_{p3})\}$$

* Step 4: Check-out Process:

$$\min\{t_{c1}, t_{c2}\}$$

In the studies conducted, it is determined that the patient is used only in the waiting room when calculating the waiting times of the patients. However, in this study, the amount of time the patient should wait for treatment to calculate the average total waiting time with four different waiting times taken into account; waiting time for officers to check-in, waiting time for nurses to triage, waiting time for the nurses or physicians to be treated, waiting time for officers to leave hospital were summed up.

$$\text{Min } Z^s_{wt} = \sum_{j=1}^n \left[\frac{d_a(w_{cj}^1 + w_{cj}^2 + w_{nj}^1 + w_{pj}) + d_n(w_{cj}^1 + w_{cj}^2 + w_{nj}^1 + w_{nj}^2)}{n} \right]$$

2.4.2.4. Average Length of Stay in this System

The sum of the average patient treatment duration and the mean patient waiting period gives the LOS value. In the following equations, the objective function is explained.

$$\text{Min } Z_{los} = \text{Min } Z_{t_t} + \text{Min } Z_{wt}$$

$$\begin{aligned} \text{Min } Z^s_{los} = \sum_{j=1}^n & \left[\frac{d_d(t_{cj}^1 + t_{cj}^2 + t_{nj}^1 + t_{pj} + w_{cj}^1 + w_{cj}^2 + w_{nj}^1 + w_{pj})}{n} \right] \\ & + \left[\frac{d_n(t_{cj}^1 + t_{cj}^2 + t_{nj}^1 + t_{nj}^2 + w_{cj}^1 + w_{cj}^2 + w_{nj}^1 + w_{nj}^2)}{n} \right] \end{aligned}$$

2.4.3. Results of the Optimization Model of the Numerical Case Research

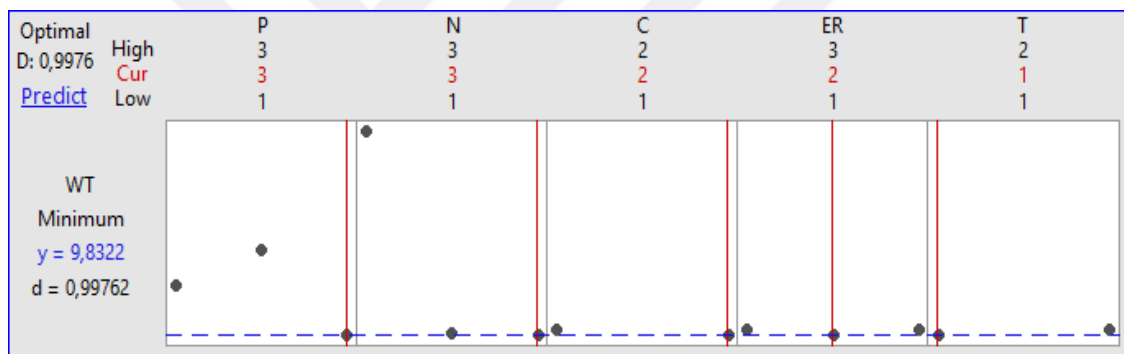
2.4.3.1. Average Waiting Time

Minimizing the waiting time for patients to be treated constitutes the objective function of this study. The feasible results are given in the Table 35 below.

Table 35: Optimum Results for Waiting Time

Factors	Optimum Result
Number of Physicians	3.00
Number of Nurses	2.00
Number of Clerks	2.00
Number of Triage Rooms	1.00
Number of Exam Rooms	3.00
Total Waiting Time	9,83221 min
Desirability	0,997618

Optimum values were obtained by considering the desirability factor (this issue was discussed in detail in the third part of this work). If these patients are required to reduce the waiting time for treatment according to this system, the decision variables are given as Figure 30's values.

**Figure 30:** Results of optimization models

Referring to Figure 31, with the increasing number of doctors, nurses and treatment rooms, the waiting time of the patient has fallen from 40.09 minutes to less than 9,832 minutes. It has been found that the number of Clerks increases the waiting time with the increase of the triage area as well as the effect on the waiting time. That is, the number of doctors, nurses and treatment rooms has a positive effect whereas the effect of triage area is negative. The effect of Clerks number seems to be neutral.

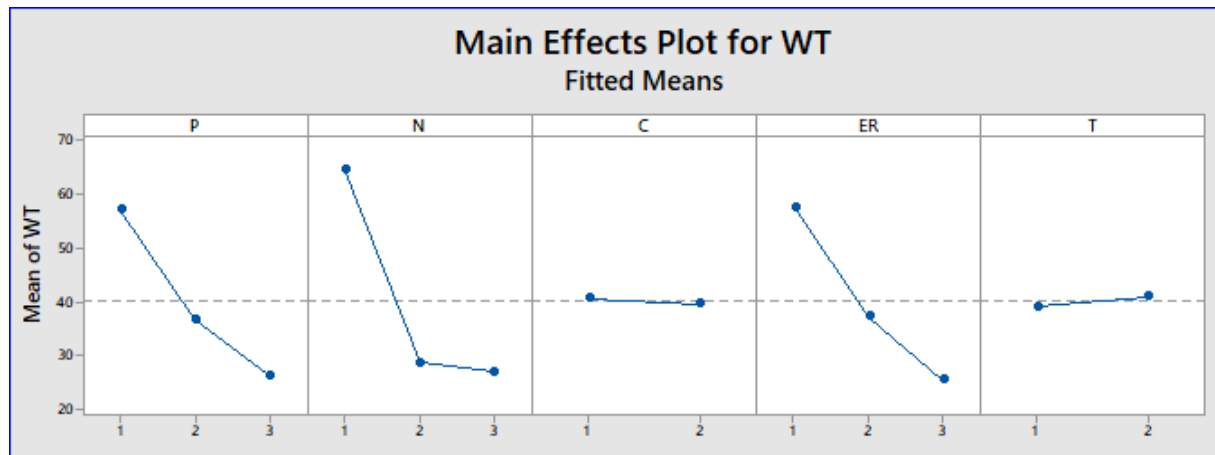


Figure 31: The effects of the main factors affecting the waiting time of the patients

2.4.3.2. Treated Patients

In this study, it was aimed to increase the number of patients treated by increasing the efficiency of existing hospital resources. Currently, the number of patients treated daily is 132 people. Based on the results of the combination of all sources, an average of 68 patients were treated. However, as a result of the improvement, the number of patients treated increased to 147. This resulted in an improvement of 11.37 % based on the average number of treated patients and a 116.18 % percent improvement over the number of treated patients according to the use of all available resources.

Table 36: Optimum Results for the Number of Treated Patients

Factors	Optimum Result
Number of Physicians	3.00
Number of Nurses	3.00
Number of Clerks	2.00
Number of Triage Rooms	1.00
Number of Exam Rooms	2.00
Total Waiting Time	146.50-147
Desirability	0.9615

In order to maximize the number of patients treated in a part of the hospital in this system, it is necessary to have the number of sources given in Table 36. In this case, the feasible results of decision variables affecting the number of patients treated with desirability factor are shown in Figure 32 of MINITAB statistical software.

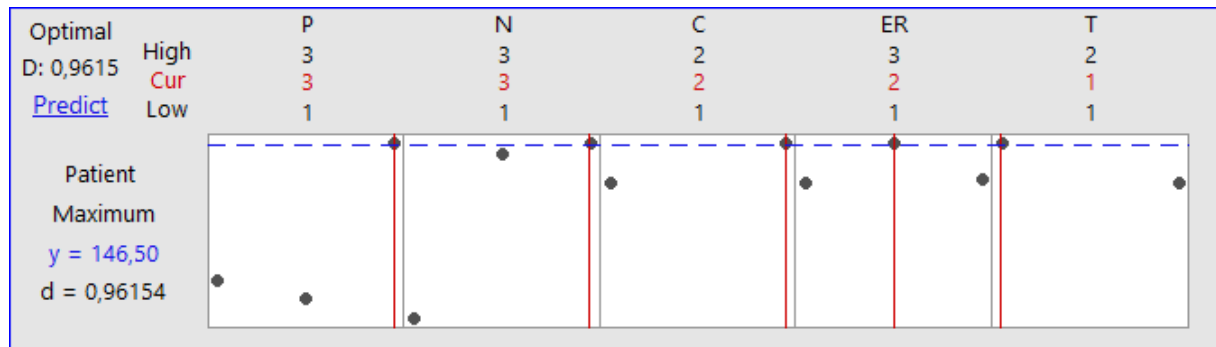


Figure 32:Optimum Factor's Numbers

There are three cases of positive, negative and neutral decision variables that affect the number of patients treated. Considering Figure 35, in the decision variables the number of physicians is the most influential factor on the number of treated patients. In the same way, the number of nurses and the number of exam rooms seem to have a positive effect. However, with the number of clerks and the number of triages appears to be a neutral effect over the number of patients treated.

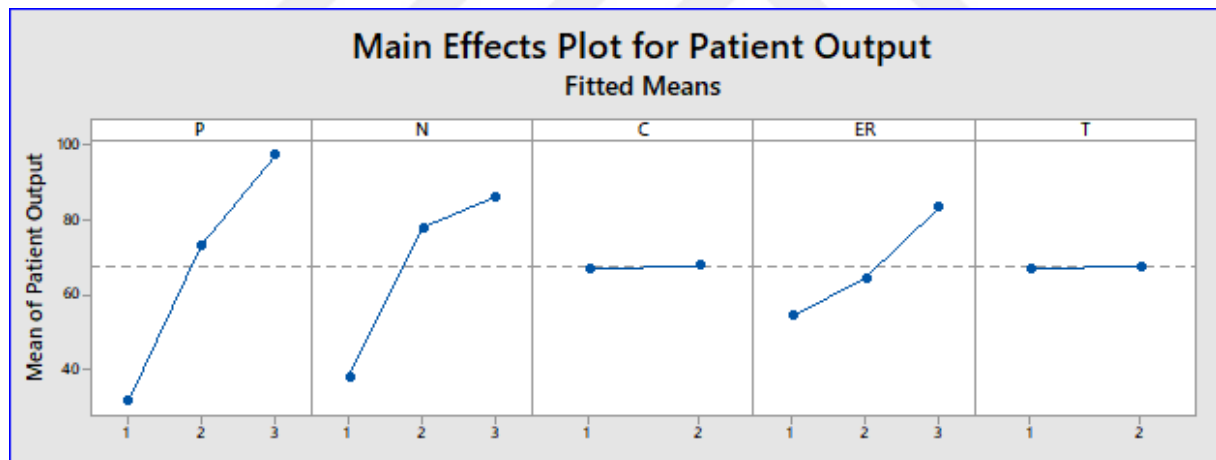


Figure 33: The Effects of the Main Factors Affecting the Number of Treated Patients

2.4.3.3. Consolidation of Patient Waiting Time and Number of Patients

In Section 2.4.3.1 and 2.4.3.2, feasible results were obtained by taking the objective functions one by one. However, in this part, both the objective functions which are that decreasing patient waiting time and increasing the number of patients treated have been considered together. The feasible results and improvements obtained are expressed in the following Table 37.

Table 37: Improvements with DOE and Simulation

Topics	Objectives	Current State Result	Average Result	Optimum Result	Improvement 1*	Improvement 2 ⁺
PO	MAX	131.5 $\approx$ 132	67.39 $\approx$ 67	146.5 $\approx$ 147	11.37%	116.76%
WT	MIN	10.75min	40.09min	9.83min	10.22%	75.480%

Note: PO-The total number of treated patients, WT-Total Waiting Time.

*: The result obtained according to current situation. +: The result based on average.

The optimal values of the resources of the clinic have been calculated to reduce the total waiting time and increase the total number of treatments to the maximum level (see Table 38). The hospitals have to incur a high volume of patients which leads to a decrease in waiting time. The results contain responses data as number of patients who are treated. All of these applications result in satisfied patients and a low cost to the government or private healthcare expenses.

Table 38: Optimum Results for the Number of Treated Patients and the Waiting Time

Factors	Optimum Result
Number of Physicians	3.00
Number of Nurses	3.00
Number of Clerks	2.00
Number of Triage Rooms	1.00
Number of Exam Rooms	2.00
The total number of treated patients	146.5~147
Total Waiting Time	9.83 min
Desirability	0.979412

Figure 34 shows the feasible values for both the waiting time and the number of patients treated. The red line on the figure moves in the direction of the values of the decision variables. The interaction of decision variables has the same effect on the objective functions. Only the relationship between the number of triages and the number of exam rooms appears to be contrary. In the direction of these results, the performance of a clinic is maximized by increasing the number of patients treated and by minimizing the waiting time.

The desirability values of the two objective functions differ. This difference directly affects the values of the decision variables and the objective function. The values of the objective function vary with decreasing or increasing desirability values. This is clearly shown in Table 39 with ten different desirability values.

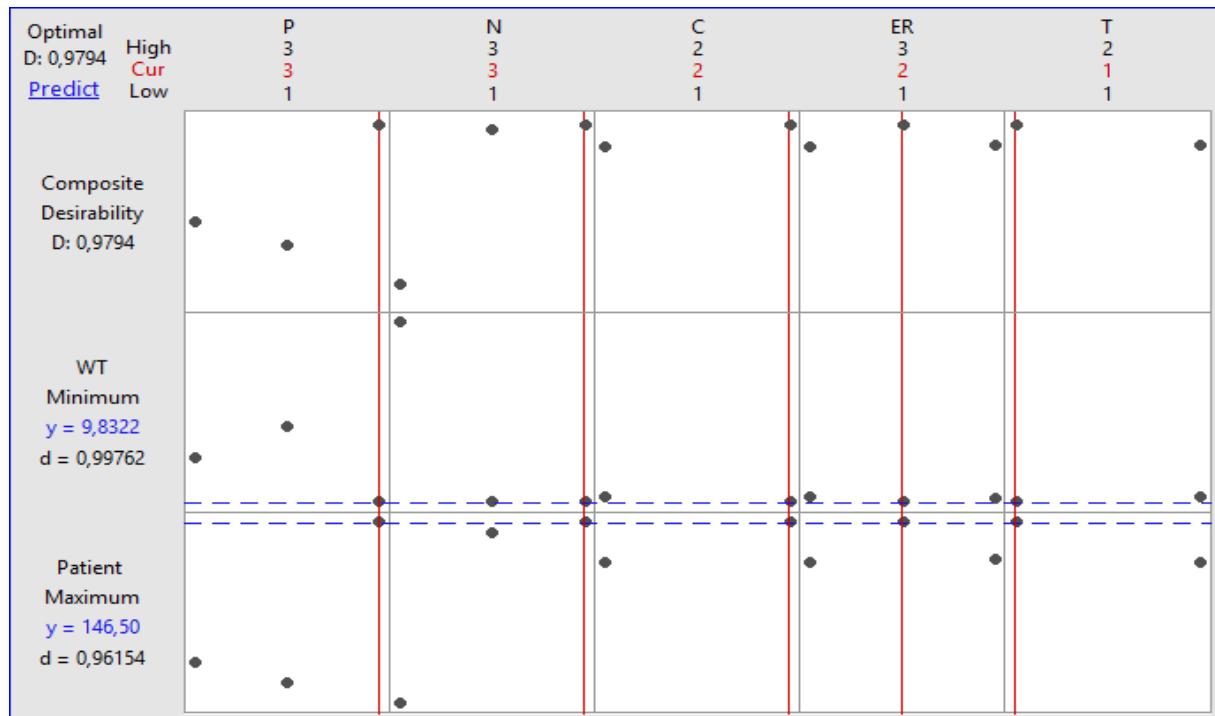


Figure 34: Results of Optimization Models

Figure 35 and Figure 36 are carefully considered, the interactions between the decision's variables affecting both objective functions multiply in a binary manner.

Table 39: 10 Optimum Results

Solutions	P	N	C	ER	T	Waiting Time	Total Treated Patients	Desirability
1	3	3	2	2	1	9,8322	146,5	0,979412
2	3	3	1	2	2	9,8649	146	0,977524
3	3	2	1	3	1	9,8797	146	0,977475
4	3	3	1	3	1	9,9568	144,75	0,972756
5	2	3	2	1	1	10,2989	140	0,954496
6	3	2	2	2	1	10,3645	139	0,950637
7	3	3	1	1	1	10,3645	139	0,950637
8	3	1	1	1	1	10,6673	135	0,93495
9	3	3	2	3	2	10,8484	132,75	0,926003
10	3	3	2	1	2	10,8484	132,75	0,926003

The relationship of decision variables to each other is either positive, negative or neutral. Generally, the interaction of decision variables has the same effect on the objective functions. Only the relationship between the number of triages and the number of exam rooms appears to be contrary.

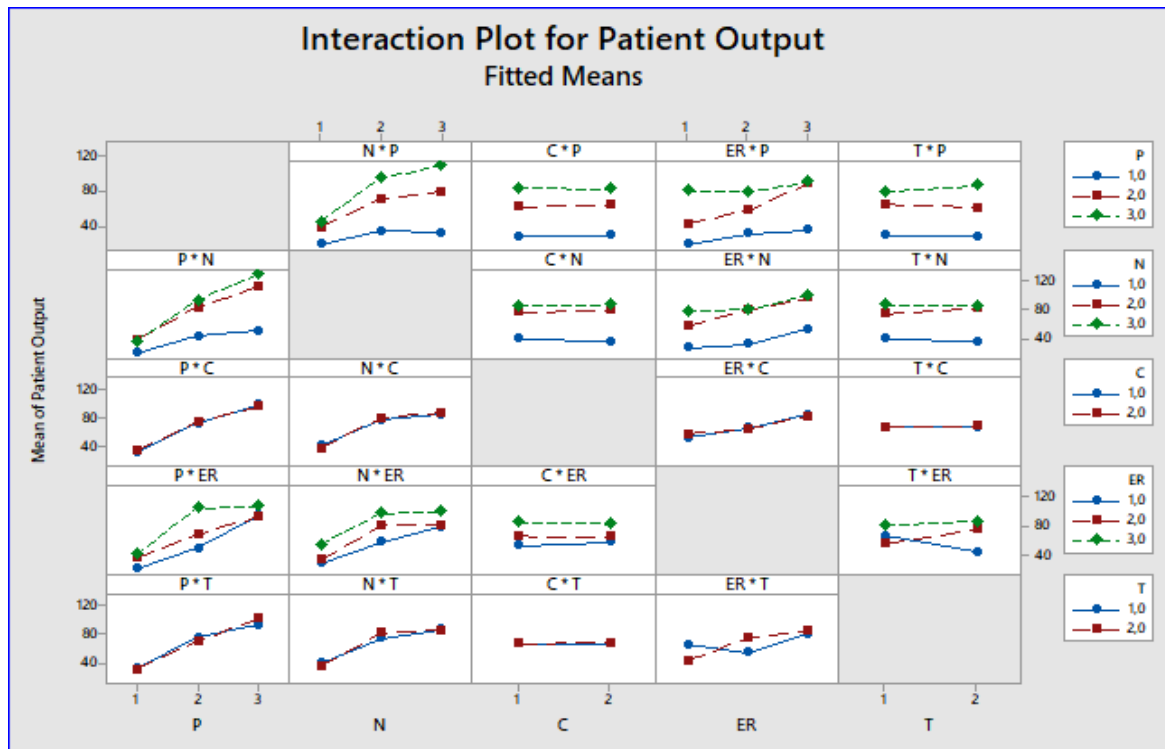


Figure 35: Effects of Factors' Interaction on the Number of Patients Treated

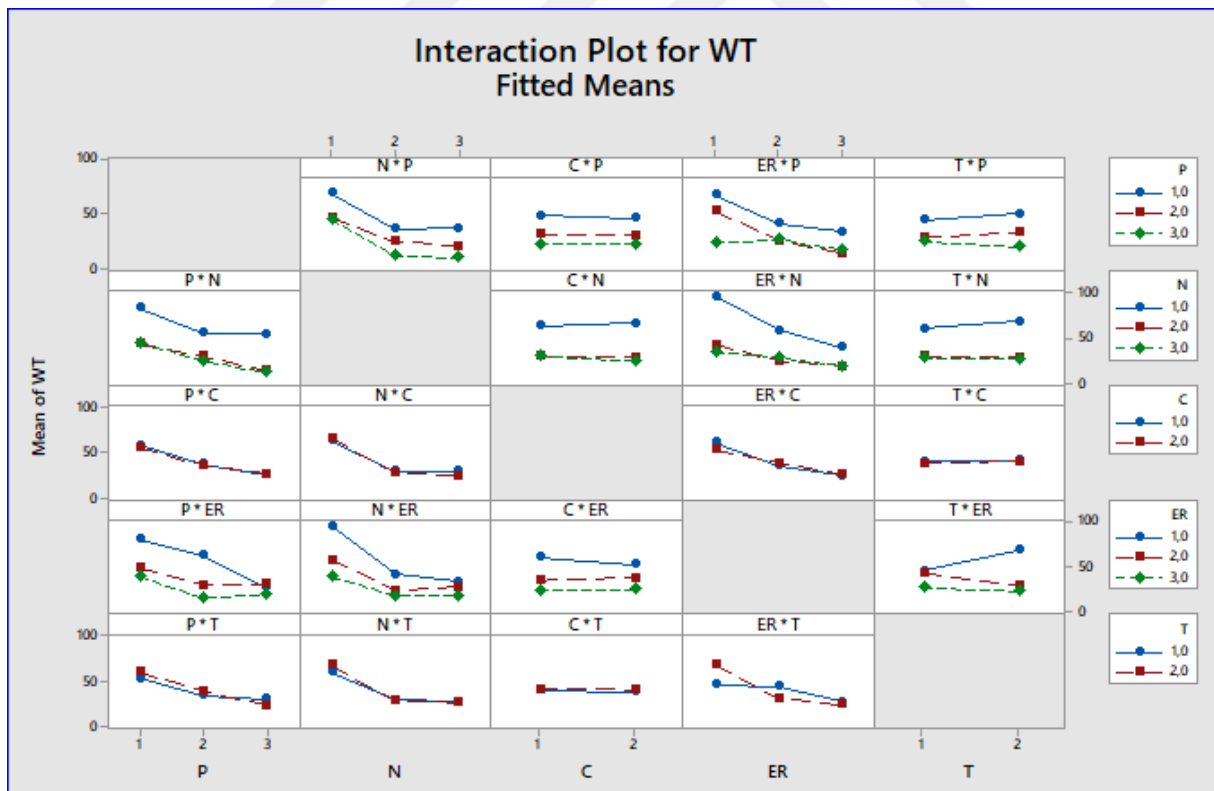


Figure 36: Effects of factors' interaction on waiting time of patients

In the direction of these results, the performance of a clinic is maximized by increasing the number of patients treated and by minimizing the waiting time.

2.5. Conclusions of Simulation with Design of Experiment in Healthcare

In industry or health environment, the main goal is to develop the potential quality for products, increase patient or customer satisfy and system or resources of health facilities performance. Many companies lost profit due to wrong applications of methods. It causes defection of products or services. In this section, DOE and Computer Simulation were used to generate data that has been determined numerically to find optimum solutions for the any hospital's departments such as emergency department, diagnostic imaging, cardiology, ear nose and throat (ENT), elderly services department, Neurology, etc. In order to maximize benefit, the optimal process should be set properly.

In this study, a simulation model of the planned system was created. By integrating the DOE approach with the simulation technique, the average waiting time of a patient in the hospital was reduced from 40.09 minutes to 9.83 minutes (improvement of 75.480 %), resulting in a significant result. The number of patients treated in one day is increased from $131.5 \approx 132$ (average) to $146.5 \approx 147$ (improvement of 11.37 %) by increasing the capacity of resources without increasing the number of available resources for any part of the hospital. With these results, both the hospital capacity and the waiting time have been reduced and patient satisfaction has been increased.

Advantages of using DOE and simulation in healthcare area explain obviously as below:

- Simulation supports to develop the healthcare process.
- Simulation agrees you to difference resources easily.
- Simulation feed understanding of the potential performance of the real system.
- Simulation benefits many advantages as decreasing waiting time, increasing resources utilization and patient satisfaction, developing patient flow.
- Simulation and DOE are very authoritative implementations to create strong decision making.
- DOE with Computer Simulation permitted a more efficient analysis of the results from the simulation model to succeed decision making.
- DOE allows for many controllable factors to be generated determining their effect on a preferred result.

It is very difficult to get accurate results everywhere where the human factor is. It seems impossible to obtain optimum results in the health system, which has a very human factor especially from the devices. Using these engineering techniques, the desired results are achieved in a very short time and at a very low cost. By using the DOE approach with the simulation technique provides to reduce the variation in the products and services. It is not appropriate to use these two techniques separately. At this point, the interaction between these two techniques leads to more concrete and detailed information. The use of these techniques in other fields is also an important reference for future studies.



Section 2: Application of Discrete Event Simulation for Emergency Department

Title: Employment of Emergency Advanced Nurses of Turkey: A Discrete-Event Simulation Application

2.1. Introduction

Healthcare is a need which is as old as human history. With the changes observed in humanity, healthcare systems have also changed in technological, quality and structural terms (Sheingold & Hahn, 2014). In hospitals, the waiting time, the length of stay, the number of patients treated, and the utilization of resources are the parameters influencing the quality of healthcare systems (Al-Abri & Al-Balushi, 2014; Bleustein et al., 2014; Fenton, Jerant, Bertakis, & Franks, 2012). In the present study, a sample simulation model was created for Turkey by considering these four important parameters.

A great number of patients, who may be treated as outpatients but which are referred to emergency services (ESs) increase the intensity of these services (Durand et al., 2012; Salway, Valenzuela, Shoenberger, Mallon, & Viccellio, 2017; I. P. Steiner et al., 2009; Uscher-Pines, Pines, Kellermann, Gillen, & Mehrotra, 2013). McGee and Kaplan claimed that 12.9% of the 12 million patients admitted to the emergency department were urgent (McGee & Kaplan, 2007). According to an article released in the Turkey Emergency Medicine Journal in 2005, 50% of the 32,800 patients who were recorded in an ES were classified as patients who were not urgent. Only about 9.9% of these patients were treated as urgent patients. The rest of these patients who have mild injuries were examined by physicians, and 1.4% were referred to the polyclinics. It was determined that 88.7% of the patients were treated as outpatients and were then discharged (Kose, Kose, Oncu, & Tugrul, 2011). These very high rates of patients being referred to ESs as urgent patients hamper the operations of ESs (Tsai, Liang, & Pearson, 2010). Recently, patients spend a certain time period in ESs even if they not urgent. These periods affect the number of patients treated, the utilization of resources, the length of stay, and the waiting times of patients at the ESs in a negative way (Unwin, Kinsman, & Rigby, 2016).

In the healthcare system of Turkey, the ESs work as follows: the patient arrives at the ES and is registered. After triage, the patient is classified according to the urgency as green zone (slight injury), yellow zone (patients who need a physician's care to prevent permanent damage but can nonetheless wait), or red zone (heavy, life threatening injury requiring immediate

examination). Then the patient is referred to the relevant unit (depending on the injury type) for doctor's examination. After examination, if it is necessary, a prescription is written, and the patient either checks out for departure or is referred to polyclinics. In such ESs, doctors work in a more intense way. The duties that are defined for nurses remain limited to the instructions given by doctors. When it is considered in the context of the chain, patients have to wait for nurses for triage, and for doctors for all other processes. This study recommends that the waiting times of the patients are reduced, and the authority of nurses is increased to reduce the number of patients that are treated in ESs.

The competencies of nurses vary according to their specific area of expertise in the healthcare systems of the United States. When the education and experience of nurses are considered, nurses are divided into four groups. The nurse group providing basic patient care like nutrition and hygiene is called nurses' assistants and aides. Such nurses become nursing assistants after receiving short-term training in hospitals or in public training centers. A nurse who completes a program that is approved by the state and who passes the related exams applied by the state or by a private center, receives the licensed practical nurse title. Such nurses are also known as licensed vocational nurses. The highest rank of nurses in the US healthcare system are in the registered nurses' group. The highest level, which is needed for patient care, is provided by a registered nurse. Such nurses, who are in direct contact with patients, observe, evaluate and record the reactions, symptoms and progress of patients. In brief, such nurses develop a nursing program for patients and manage it. Furthermore, practitioner nurses provide patients with the highest patient care. For the purpose of becoming an advanced practice nurse, registered nurses must have a postgraduate degree in the field of clinic specialty. Doctors have the authority to write prescriptions to patients in an independent manner without any cooperation or supervision. However, their authority for writing prescriptions is restricted by the laws of the states they work in, and the drugs they may prescribe are controlled by these laws (Austin & Wetle, 2016).

In previous studies, only two parameters, patient waiting time and length of stay, were taken into consideration in examining the effect on quality of healthcare that is determined according to treatment cost and patient's satisfaction (Dukhanin et al., 2018; Woo, Lee, & Tam, 2017). In this study, four different parameters—waiting time, the length of stay, the number of patients treated, and the utilization of resources in ESs—were examined by a different method. These parameters are in direct interaction with each other. A study of Canadian emergency

departments made observations of patients who were examined by practice nurses. The number of patients examined by these nurses instead of physicians increased by 12% and the average waiting time decreased by 7 minutes (I. P. Steiner et al., 2009). In another study, it was observed that in an ES with three categories (Category 3, 4, and 5) with the implementation of the practice nurses model (i.e., increasing the knowledge and skills of ESs by providing extra education and training to normal nurses), the patients' waiting time was reduced by 1 minute (Category 3: 28 to 27 minutes, Category 4: 35 to 34 minutes, Category 5: 27 to 26 minutes) (Plath, Bratby, Poole, Forristal, & Morel, 2018). In another study, in an emergency department for analgesia process, 130 of 258 patients were consulted by practice nurses, and the remaining patients were consulted by physicians. According to the results, the time required for patients to be administered drugs by practice nurses was shortened by 8 min compared to administration by physicians (M. T. A. Steiner, Datta, Neto, Scarpin, & Figueira, 2015). Some studies suppose that the efficiency of doctors with practice nurses is high in ESs. A study showed that the satisfaction rates of patients treated by a doctor and a practice nurse working together was increased in an ES in Austria. Out of 320 patients, the satisfaction rates were measured as 84% according to the survey form. However, patient waiting and stay times were not taken into consideration (Dinh, Walker, Parameswaran, & Enright, 2012). In a small emergency department in Australia, 61 patients were examined by physicians with the help of emergency nurses, and the waiting time and length of stay were calculated as 13.2 minutes and 116 minutes, respectively. Nevertheless, no evidence is provided in terms of comparison with other situations related to these parameters in the research (Roche, Gardner, & Jack, 2017).

The purpose of this study is to ensure that nurses recommended for ESs in Turkey are employed as advanced nurses (ANs) after receiving 2+ years of training after they complete a normal nursing education. ANs must have the authority to write prescriptions for routine diseases (colds, headaches, influenzas, diarrhea, fever, weakness, etc.). The drugs they may prescribe to patients may be limited by the state and thus taken under control. Since such patients may be treated as outpatients, they are under the authority of ANs.

Using simulation techniques in the healthcare field dates as back as the 1970s (England & Roberts, 1978). Whether simulations are discrete or continuous depends on the data type that is used for the simulation. The type of simulation used in the healthcare field is mostly the discrete event simulation technique (Günel & Pidd, 2010). The reason for this is that such simulations differ according to working durations, which are determined as daily, weekly,

monthly or yearly. In general, it is observed that the discrete simulation technique has been used in the healthcare sector for three purposes: planning the resources of hospitals (doctors, nurses, beds, civil servants, etc.), planning the shifts of the staff in hospitals, and planning patient-flow diagrams. The studies in which patient simulation modeling was performed were also covered in this scope (Gupta & Denton, 2008).

The use of discrete simulation models is common in ESs (Ceglowski, Churilov, & Wasserthiel, 2007; Connelly & Bair, 2004; Raunak, Osterweil, Wise, Clarke, & Henneman, 2009). In the simulation models that were developed, the purpose was to reduce the waiting durations of patients (Komashie & Mousavi, 2005; Mandahawi, Shihabi, Abdallah, & Alfarah, 2010). In one study, a total of 517 patients were observed in pediatric emergency services in order to develop a new patient flow to reduce the waiting times of patients by applying simulations and by adding to the number of employees (Hung, Whitehouse, O'Neill, Gray, & Kissoon, 2007; Wang, Guinet, Belaidi, & Besombes, 2009). Simulations were applied in studies that aimed to improve the capacity of ESs.

The most important factor that distinguishes this study from other studies is the method used, which is discrete event computer simulation for ESs. Despite most studies being based on surveys and observations, more tangible and accurate results were obtained by using numerical data in this study. The findings contribute positively to physician recruitment, patients' and employees' satisfaction, quality of healthcare service, and healthcare costs, by employment of ANs (a new profession between physicians and normal nurses).

In this study, comparisons were made by creating a simulation model with and without ANs. The simulation method was used to obtain the results of the study in an accurate and quick manner without costs. Simulation models are expressed by decisional analytical modeling (van Gestel et al., 2010). It is a required situation that the simulation models are flexible and understandable for the user and for the decision problems created for healthcare systems. The reason why simulation models developed in the field of healthcare are complex is that they contain successive combinations. The uncertainty is minimal in the work flow that is defined in any production or transport simulation. For example, the fact that there is a robot/machine factor instead of a human factor in the automotive manufacturing sector minimizes the variability rates in production. However, this situation is not valid for the healthcare field. The presence of changes in patient flow-charts and uncertainties for the next process increases the

variation in developed simulation models. As the treatment type that will be applied to the patient arriving at the ES cannot be predicted, it is required that simulation models are applied, and more than one strategy is developed and compared.

The present study consists of four main sections. In the first section, information is provided on the functioning of ESs, and the types of nurses and the simulation methods that are applied. In the second section, information is provided on the method applied in the present study. The determination of the patient flow-charts and the data that are needed for the creation of the simulation model is carried out in this section. In the third section, the comparison of data is made for the simulation models. In the final section, the conclusion of the study is given.



2.2. Materials and Methods

In this study, the purpose was to reduce the waiting times and length of stays in ESs in Turkey, to make the resources of the ESs efficient, and to increase the number of patients who are treated. It is emphasized that great changes are made in the working and branching rules of the nurses in Turkey, and an AN class is created to treat patients who are not really urgent and who are outpatients. It was ensured that concrete results were obtained with numerical data by applying a discrete event simulation sample. This section comprises four headings, which follow.

2.2.1. Specifications, Authorities and Rights of ANs

It was emphasized in this study that each nurse should be given additional training and internship in the fields in which s/he desires to become specialized. Article 4 of the Nursing Law 6283—“the duties, authorities and responsibilities of nurses are regulated by the Ministry of Health according to the working areas, positions and educational status in the services that were listed in the first paragraph of the law”—supports this study (Türk-Tabibleri-Birliği., 2007). In this study, it is mandatory for nurses identified as ANs to have the following specifications:

Educational Characteristics:

- Completion of 4-year basic nursing education at university.
- Passing the entrance examination of postgraduate education after university.
- Completion of postgraduate education.
- Passing the examinations that will be held at regular intervals to renew AN certificate.

Authorization:

- Being employed in ESs.
- Treating patients without the need for cooperation with doctors for certain diseases.
- Being able to write prescriptions for drugs defined by laws.
- Auditing other nurses.

Social Rights:

- Having the same shifts and working hours as normal nurses.
- Receiving a salary that is higher than normal nurses but lower than doctors.

- Having other social rights provided by the Ministry of Health.

2.2.2. ES Patient Flow Diagrams

In this section, the working principles of the ESs in the healthcare system of Turkey are dealt with. In general terms, the patient flow in ESs is given in Figure 37. According to Figure 1, the patient is referred to green, yellow and red areas in ESs according to the type of the disease after triage. The patients wait for the doctor to treat them after they are referred to relevant units, and they are either kept waiting at short-stay units after they are treated or are referred to polyclinics or receive written prescriptions to be discharged. In the present study, comparisons were made to measure the effect of the AN factor by creating two different models based on the single simulation design. The patient flow given in Figure 37 was used in the first simulation model. To facilitate the understanding of the simulation model and the outcomes, the yellow, green and red zones were taken as single fields.

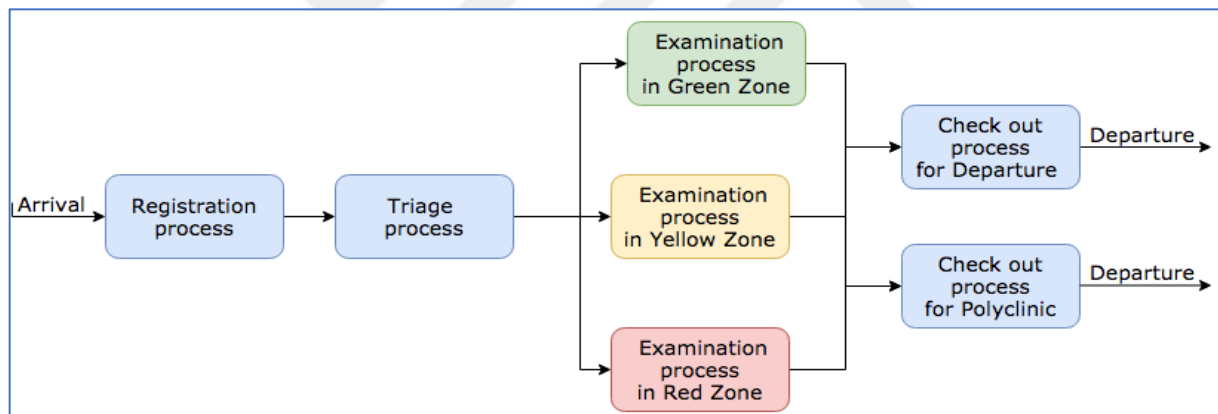


Figure 37: Emergency service (ES) patient flow diagram

According to the second simulation model, the difference in this patient flow-chart is that if a patient has a disease type which may be treated by an AN after normal triage is completed, s/he is examined in the triage field and, then, s/he is either discharged or referred to a polyclinic. It is not the case that a patient who is examined by a AN is examined again by the doctor. The patient is referred to the doctor according to his/her urgency and to the type of his/her disease; and after s/he is examined by the doctor, s/he is either referred to the polyclinic or is discharged. In this situation, each patient will not have to wait for the doctor.

2.2.3. The Data Used in the Simulation

In the present study, the 3D Flexsim-Healthcare (HC) Program was used with the discrete simulation technique. This program is a computer-based model of activities that pays attention to the physical structure of a real healthcare department. The Flexsim-Healthcare simulation program is a graphical model with an animated background and a hierarchical configuration. It is an object-oriented method which permits the professional user to categorize the resources of the system for the end-user. This program was preferred because it is easy to follow-up with the icons, and the program allows the user to manage the movements of patients and staff. The distributions needed for the processes in the patient flow were obtained from an institution that provides healthcare in Turkey according to a 24/7/365 working schedule. The data were collected by healthcare professionals in the computer medium based on observations (Electronic Medical Record (EMR) Software).

The data that were employed in the present study were followed-up for two years. The reason for the long-term data collection is the behavior-movements of humans, who are the main actors in healthcare sector. To obtain absolute and accurate results, the data must be considered as seasonal (summer–winter–spring). In this way, the dimension of the correlation between the data that are collected in the first year and those collected in the following year may be measured. In the present study, the distributions of the data were determined with the Flexsim-HC ExpertFit tool. The data that were used in the first simulation model are given in Table 40.

Table 40: The data used for simulation with/without advanced nurse (AN) factor

Parameters of Simulation	Distribution	Minimum Value	Mean Value	Maximum Value
Arriving Patient	Exponential (0.0, 10.0, 0)	--	10.00	--
Check-in	Uniform (3.0, 5.0, 0.0)	3.00	--	5.00
Triage	Triangular (3.0, 15.0, 5.0)	3.00	5.00	15.00
Treatment by MD*	Uniform (20.0, 30.0, 0.0)	20.00	--	30.00
Treatment by AN	Triangular (3.0, 15.0, 5.0)	3.00	5.00	15.00
Check-out	Uniform (3.0, 5.0, 0.0)	3.00	--	5.00
The rate of patients treated by MD*	p	5.00%		95.00%
The rate of patients treated by AN	$1-p$	5.00%		95.00%

*Medical Doctor

In the second simulation model, a percentage rate (p) must be used because the AN factor was considered. The parameter that determines this rate is the number of patients who arrive at ESs and who are not urgent (the patients examined by ANs) and the urgent patients (the patients examined by doctors).

The resources that were used in the simulation models (doctors, nurses, beds, triage units, registration, and the attendants performing discharge procedures) belong to a small-scale ES. The number of ES resources that were employed in both simulations is fixed: 3 doctors, 3 nurses, 6 beds, 3 triage rooms or units, and finally, 2 attendants who performed the arrival–discharge proceedings. Only in the simulation model that had the AN factor, 1 nurse (2 normal nurses + 1 AN) was determined from among 3 nurses. In the model, external resources were not added.

2.2.4. Creating the Simulation Model

The two different situations that were considered in the application stage of the study are shown in the single simulation model. The purpose was to compare the simulation model with and without the AN factor. For both cases, the simulation models were repeated 3 times for a total of 58 times (19 scenarios with the AN factor, and 1 scenario without the AN factor were considered). Since the simulation parameters were not updated before each application (the scenarios were run one-by-one) in the Flexsim-HC program, change during the warm-up stage was prevented to avoid data loss and biased results with instant warm-up periods. In finite horizon simulation models, certain starting and ending conditions were considered; for this reason, in the present study we did not enter the warm-up period data (warm-up periods are employed in infinite models). The observations are independent in such simulation models. When different outcomes were obtained, random simulation numbers were run with the same initiation conditions. The simulation model was operated on a daily basis, and on a 1-week basis with 1/24 and 7/24 working principles. A screenshot of the simulation model is given in Figure 38.

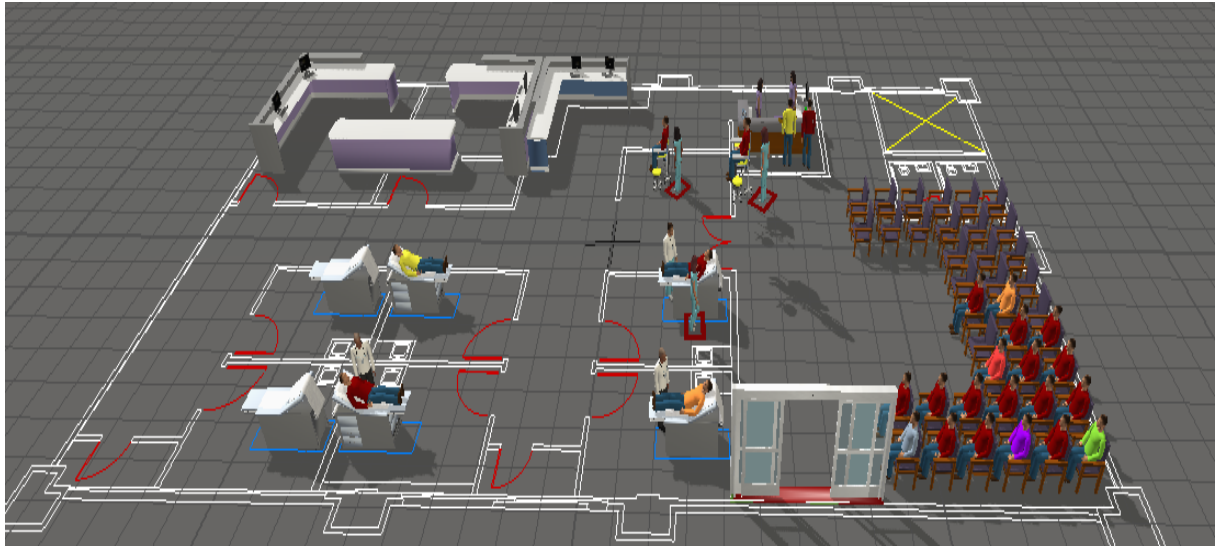


Figure 38: Screenshot of the simulation for ES

As the simulation program that was employed was 3D, it worked more slowly compared to the other simulation programs. The C++ computer programming language was used to develop this simulation model for the healthcare field. The patients were treated according to the patient flow-chart for the normal and AN scenario of the simulation model to perform the activities given in Table 41 and

Table 42.

Table 41: Patient flow for the first model of the simulation

Activity	Name	Type	Process Time	Patient Destination
10.00	Arrival	Patient Travels Unattended	0.00	Waiting Room Area
20.00	Go to Registration	Patient Travels Unattended	0.00	Registration Area
30.00	Registration	Process	uniform (3.0, 5.0, 0.0)	Registration Area
40.00	Waiting Room	Patient Travels Unattended	0.00	Waiting Room Area
50.00	Escort to Patient Triage	Escort Patient	0.00	Triage Area
60.00	Triage Exam	Process	triangular (3.0, 15.0, 5.0)	Triage Area
70.00	Escort to Waiting Room	Escort Patient	0.00	Waiting Room Area
80.00	Escort to Exam Room	Escort Patient	0.00	Exam Rooms
90.00	MD Exam	Process	uniform (20.0, 30.0, 0.0)	Exam Rooms
100.00	Go to Waiting Room	Patient Travels Unattended	0.00	Waiting Room Area
110.00	Go to Check Out	Patient Travels Unattended	0.00	Registration Area
120.00	Check Out	Process	uniform (3.0, 5.0, 0.0)	Registration Area
130.00	Departure	Patient Travels Unattended	0.00	Patient Exit Area

Table 42: Patient flow for the AN model of the simulation

Activity	Name	Type	Process Time	Patient Destination
10.00	Arrival	Patient Travels Unattended	0.00	Waiting Room Area
20.00	Go to Registration	Patient Travels Unattended	0.00	Registration Area
30.00	Registration	Process	uniform (3.0, 5.0, 0.0)	Registration Area
40.00	Waiting Room	Patient Travels Unattended	0.00	Waiting Room Area
50.00	Escort to Patient Triage	Escort Patient	0.00	Triage Area
60.00	Triage Exam	Process	triangular (3.0, 15.0, 5.0)	Triage Area
70.00	Decision Exam by Nurse or MD	Decision Point	***	***
80.00	Exam by Nurse in Triage Area	Process	triangular (3.0, 10.0, 5.0)	Triage Area
90.00	Escort to Waiting Room	Escort Patient	0	Waiting Room Area
100.00	Escort to Exam Room	Escort Patient	0	Exam Rooms
110.00	MD Exam	Process	uniform (20.0, 30.0, 0.0)	Exam Rooms
120.00	Go to Waiting Room	Patient Travels Unattended	0.00	Waiting Room Area
130.00	Go to Check Out	Patient Travels Unattended	0.00	Registration Area
140.00	Check Out	Process	uniform (3.0, 5.0, 0.0)	Registration Area
150.00	Departure	Patient Travels Unattended	0.00	Patient Exit Area

2.2.5. Objective Result Definitions in the Simulation

The discrete event simulation program was applied to obtain the results without/with ANs which are given in Table 43, Table 48, and Table 49, respectively, for the parameters of the study. Increasing the number of patients treated and the utilization of resources and decreasing the patient's waiting time and length of stay in the ES are defined as the objectives of this study. The explanations of how to gain the objective results of the parameters are included in the following subsections.

2.2.5.1. Number of Patients Treated

According to the model, the number of the patients was computed for 1/24 and 7/24. In the simulation models, the number of the patients that were treated was computed as the final stage of the patient flow. The number of patients that were computed for the ES in the second simulation model was related to the patient percentage $(1 - p)$ treated by the AN staff. The average number of the patients that were treated by the AN staff was 146 (1/24) and 1059 (7/24), which means that the number of the patients treated by the ANs was different in terms of percentages.

2.2.5.2. Patient Waiting Times

The patient waiting times for the two models of the application were compared. The patient waiting times were not considered only for the waiting rooms. Seven different waiting times were determined and are explained as follows:

- w_r , waiting time for the attendant to be registered
- w_n , waiting time for the nurse for triage
- w_t , waiting time for the triage unit to be suitable
- w_b , waiting time for the beds used in examination to be suitable
- w_d , waiting time for the doctor for examination
- w_{an} , waiting time for the AN for examination
- w_e , waiting time for the attendant for discharge.

Since the rate of the number of the patients examined by doctors and nurses was expressed with p , the waiting times were given as w_{dn} :

$$w_{dn} = p * w_d + (1 - p) * w_n \quad (60)$$

If the average waiting time (w_a) that was obtained by considering these times is formulated in mathematical terms, the following is obtained:

$$w_a = w_r + w_n + w_t + w_b + w_{dn} + w_e \quad (61)$$

The waiting times are directly related to the processes given in the patient flow-charts. However, the hidden waiting times are not considered in studies conducted with discrete simulation models; for example, if a patient whose triage process is completed is immediately sent to an empty bed and is examined by a doctor immediately if there is a suitable doctor, or

if the patient has to wait in the patient bed until a doctor is available. These waiting times are described as hidden waiting times. In the present study, the computations were made by considering these times. The average waiting time of a patient was 39.07 minutes in the simulation that was operated without AN staff. The waiting times in the simulation that was operated with AN staff are given in Table 48 and Table 49.

2.2.5.3. The Length of Stay in ESs

In ESs, there are waiting times for patients to be examined both for treatment and to initiate the processes. By adding these periods, the time that a patient has to spend in ESs is computed. In this study, the times of the processes that patients have in the patient flow-chart were entered in the model as a statistical distribution. The times of the processes given in the patient flow-charts that were created for the initiation of the first situation of the simulation model are given below:

- t_r , the time needed for registration process
- t_t , the time needed for triage process
- t_p , the time needed for examination process
- t_e , the time needed for discharge process.

By considering the total time t_s taken by these processes, it is formulated in mathematical terms as follows:

$$t_s = t_r + t_t + t_p + t_e \quad (62)$$

A new waiting time must be identified by adding the second situation of the simulation model, which is with the AN factor. The time needed for AN and doctors were expressed as t_{an} and t_d , respectively. However, this time must not be considered as an additional time because it is related to the rate of the total time that constitutes the time for being examined for the patients by doctors. The new examination time t_{p2} is formulated in mathematical terms as follows:

$$t_{p2} = p * t_p + (1 - p) * t_{an} \quad (63)$$

The total time of a patient spent in ES is given in Equations (64) and (65):

$$t_{sum} = t_r + t_t + t_p + t_e + w_r + w_n + w_b + w_d + w_{an} + w_e \quad (64)$$

$$t_{sum} = t_r + t_t + t_{p2} + t_e + w_r + w_n + w_b + w_t + w_{dn} + w_e \quad (65)$$

The stay of a patient in the ES was calculated as 74.29 minutes in the first case of the simulation model. It was determined that this time was more than the maximum time that was computed for the first situation. When the number of the patients arriving at the ES and examined by ANs in the second situation is considered as a percentage, the average stay of a patient varies in the ES.

2.2.5.4. Working Performances of the Resources of the ES

In the present study, the analysis and comparisons of the two different situations were made without changing the resources used for ES simulations. Only one of the three nurses who were included in the first scenario of the simulation model was evaluated in the AN staff and was used for the second model. No change was made in the total quantity of resources.

The efficiencies of the resources that were present in the hospital units was measured in percentiles. The method that was employed in the computations for productivity was computed with the time spent with patients or with the number of patients. The efficiencies of five different health resources was examined for the numerical analyses in this study. Comparisons were made for both simulation model situations by computing the efficiencies of the attendants for doctor, nurse, bed, triage, and registration–discharge processes.

2.3. Results and Discussion of Numerical Data from the Simulation

Two results were obtained with the data that were employed in the simulation model. The results that were obtained when the simulation was run for one day and for one week were compared. The results that were obtained for the first situation of the simulation model are shown in Table 43.

Table 43: The results obtained for the normal situation of the simulation model.

Parameters	1/24 Operating	7/24 Operating	Differences
Waiting Time	33.243 min	44.89 min	11.647 min
Length of Stay	75.946 min	88.99 min	13.044 min
Number of patients treated	146.00	1090.00	9.71
Utilization of Physicians	85.72%	90.38%	4.66%
Utilization of Nurses	32.65%	32.49%	0.16%
Utilization of Clerks	42.04%	43.47%	1.43%
Utilization of Triage Area	31.03%	30.56%	0,47%
Utilization of Exam Rooms	57.72%	61.44%	3,72%

Based on the data that are given in Table 43, the average waiting times of patients vary between 33.24 minutes and 44.89 minutes. The average duration of hospital stay of a patient varies between 75.95 minutes and 88.99 minutes. When the AN factor was not considered, the average rate of the work of doctors was over 90%. However, low nurse and triage area efficiency was an expected situation. High rates of working of a resource leads to a decrease in the intensity of other resources because it is necessary that the patient-flow processes follow each other in a successive way, and the processes act according to a certain plan.

In Table 4, there is a similarity in the results that were obtained at the end of a one-day and one-week running of the simulation model. The average number of patients who were treated was 146 in one day, and the difference between the number of patients who were treated in one week was very close. There was approximately 12.01 minutes' difference between running the one-day simulation model and the one-week run in terms of waiting periods of patients. Similarly, the difference between the stay of patients including the waiting time for examination was computed as 13.04 minutes. It was determined that the efficiency rates of the hospital resources were close to each other. A total of 19 scenarios were examined for the second

situation of the simulation model. Comparisons were made between the data that were received from the simulation model and the initial data in the scenarios produced within the model. Figures of the study were created by *numbers* software to organize and summarize the Table 48 and Table 49 statistically.

2.3.1. Results from Running the Simulation Model 1/24

In Figure 39, the effect of AN employment on waiting times with the change in the rate of patients that were treated by AN staff is given. For the purpose of keeping the R^2 value high in the figure, the curve shows a polynomial distribution with a fifth-degree equation. The equation that shows the waiting times of patients is formulated as below:

$$y_{wt}^{1/24} = -0.0007x^5 - 0.0467x^4 - 1.1495x^3 + 14.136x^2 - 87.454x + 224.03 \quad (66)$$

According to the equation, the response variable $y_{wt}^{1/24}$ (average waiting time on basis of 1/24) is only connected with the rate of patients treated (x) by AN. According to the figure, when 50.00% of the patients arriving at ESs were examined by AN, the waiting times of patients decreased to the minimum level. The average waiting time of the 19 scenarios was 20.59 minutes.

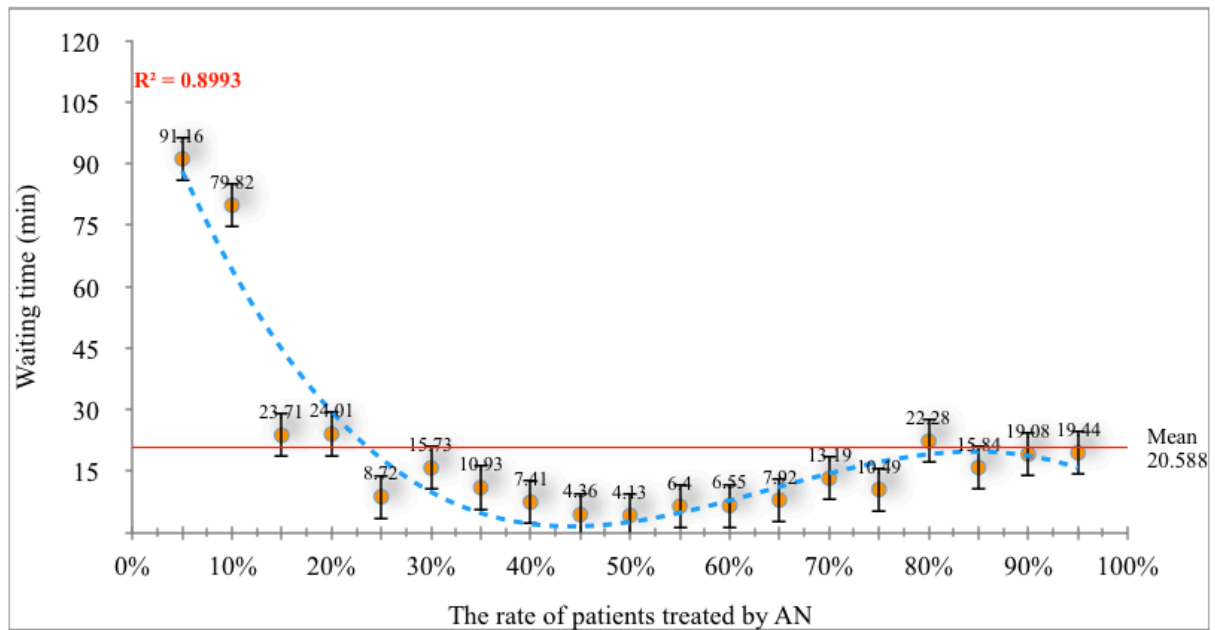


Figure 39: The effect of rate on the waiting time of the patient treated by HSN based on 1/24

The total number of the patients treated for each scenario of the second situation of the simulation model is given in Figure 40. The R^2 value of the data is lower as compared to the

other parameters' results. The reason for this is that the number of patients in the simulation model is not associated with the number of the patients being referred to ESs, but with the number of patients who are discharged, $y_{po}^{1/24}$. The line that was drawn for the data seems to be a polynomial sixth-degree curve. The equational explanation of this curve is given below:

$$y_{po}^{1/24} = 6949.5x^6 - 22608x^5 + 26862x^4 - 14090x^3 + 3109.3x^2 + 218.52x + 184.43 \quad (67)$$

After running the simulation model, the average number of patients examined for all scenarios was computed to be 185. This result is higher than the result of simulation model without AN, in which 26.71% more patients were treated with AN.

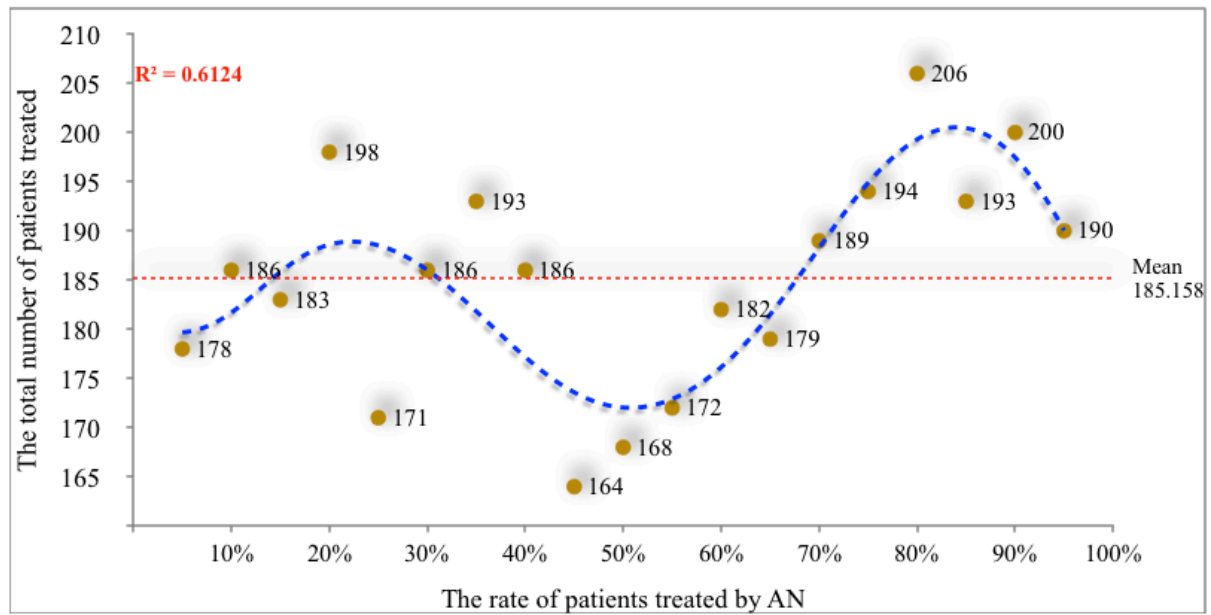


Figure 40: The effect on the number of patients treated by HSN based on 1/24

The minimum level of the length of stay was observed when the rate of the patients treated by AN was approximately 50.00% in Figure 41. The average length of stay was determined as 53.75 minutes. This time is far below the value of the 1/24 basis in the simulation model, and a 41.85% reduction was achieved in comparison to that without AN.

The data on the length of stay, $y_{los}^{1/2}$, has a non-linear fourth-degree polynomial equation to achieve a high value of R^2 . The equation for the length of stay is given below:

$$y_{los}^{1/24} = 0.0056x^4 - 0.3146x^3 + 6.4825x^2 - 56.876x + 218.64 \quad (68)$$

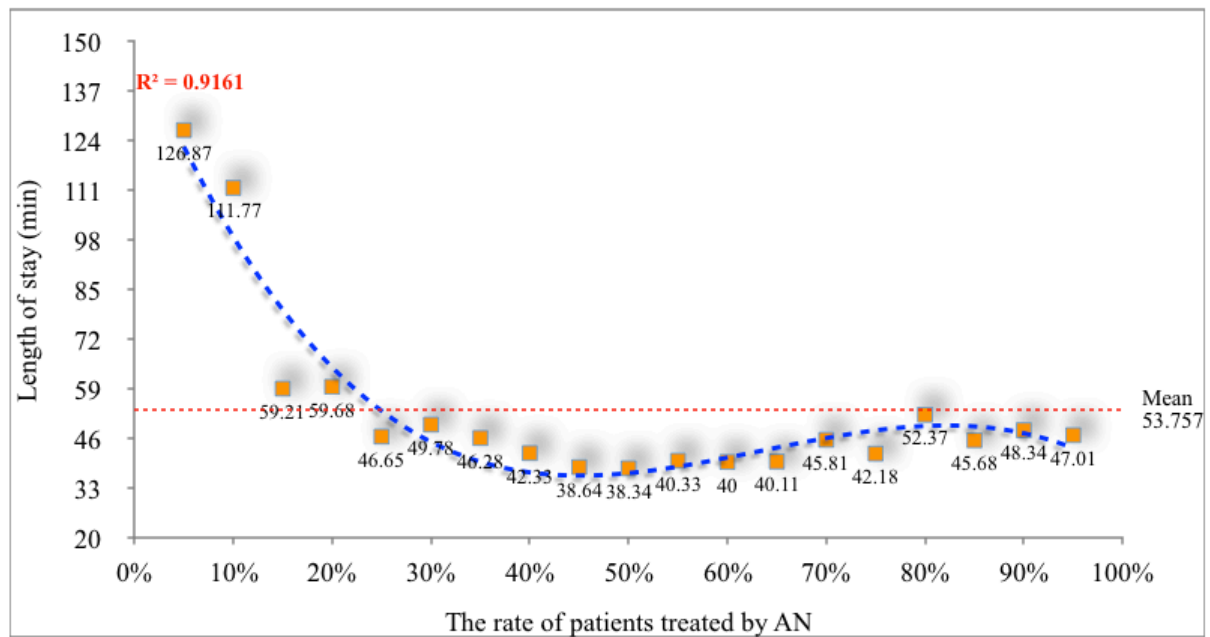


Figure 41: The effect of the rate of patient treated by HSN on the LOS based on 1/24

The changes in the efficiency rates of the resources (except equipment) of ES that were employed in the face of the AN factor are given in Figure 42. Since the efficiency rates that are shown for five resources (medical doctors, MD; nurses, N; clerks, C; exam rooms, ER; and triage units, TR) are close to each other, it may be stated that there is a strong correlation between them.

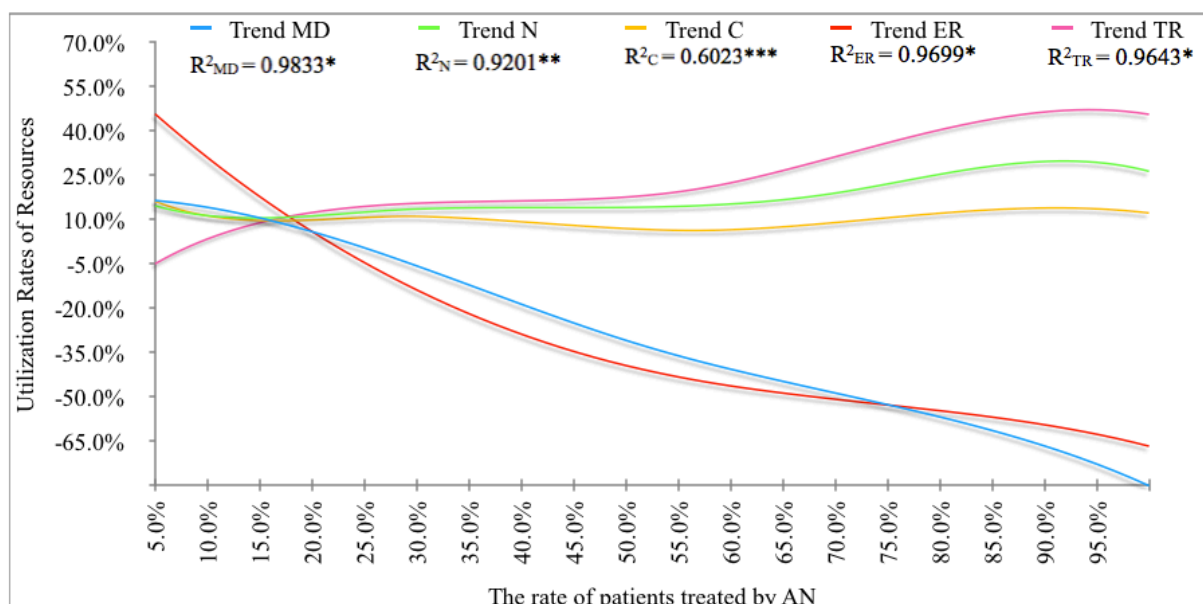


Figure 42: Effect of YUH employment on resources based on 1/24

Note: *, ** and *** are expressed as fourth-, fifth- and sixth-degree nonlinear curves with high R^2 , respectively.

With the increase in the rate of patients treated by AN, the decrease in the intensity of doctors and exam rooms is a desired result. In particular, it was determined that the intensity rate of doctors may be reduced by employing AN. The utilization rates of the rest of the resources show a horizontal trend.

2.3.2. Results Obtained When the Simulation Model was applied for 7/24

This part of the study considered the simulation model that was run on the 7/24 basis, the purpose of which was to obtain the best curve and equation to have a high R^2 ratio.

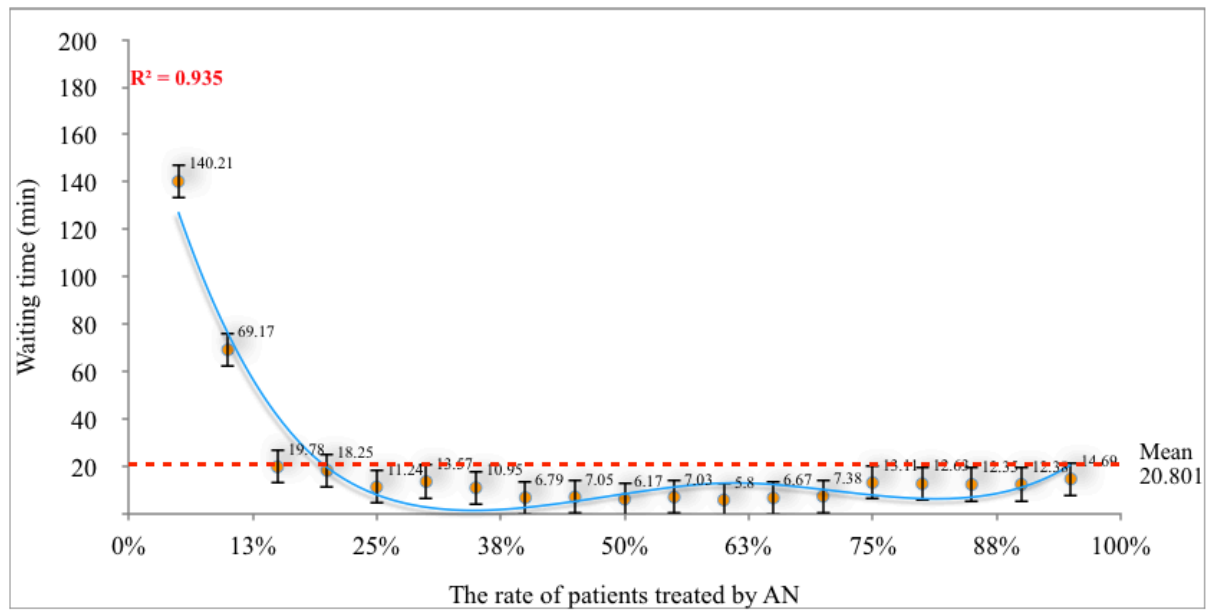


Figure 43: The effect of rate on the waiting time of the patient treated by HSN based on 7/24

The impact of the rate of patients treated by AN on the waiting times of the patients, $y_{wt}^{7/24}$, is given in Figure 43. The waiting time of a patient was calculated as 20.801 minutes on 7/24 basis with the help of AN resource and a 53.66% reduction was achieved in comparison to that without AN. The following equation was obtained from a fourth-degree parabolic equation with a high R^2 :

$$y_{wt}^{7/24} = 0.0157x^4 - 0.7997x^3 + 14.496x^2 - 109.48x + 294.41 \quad (69)$$

The relationship between the rate of patients treated by AN on 7/24 basis and the total number of patients treated is given in Figure 44. The polynomial equation obtained on the basis of 7/24 with a sixth-degree equation was observed to have the same characteristics as on the

basis of 1/24 with the polynomial equation. The sixth-degree non-linear equation that was obtained is formulated as:

$$y_{po}^{7/24} = -14,363x^6 + 36,118x^5 - 32,583x^4 + 12,993x^3 - 1350.9x^2 - 194.53x + 1277.8 \quad (70)$$

The average number of the patients, $y_{po}^{7/24}$, that was treated by ANs was computed as 1255. This result was 15.13% more than the number of the patients treated in the normal situation that does not include AN resource.

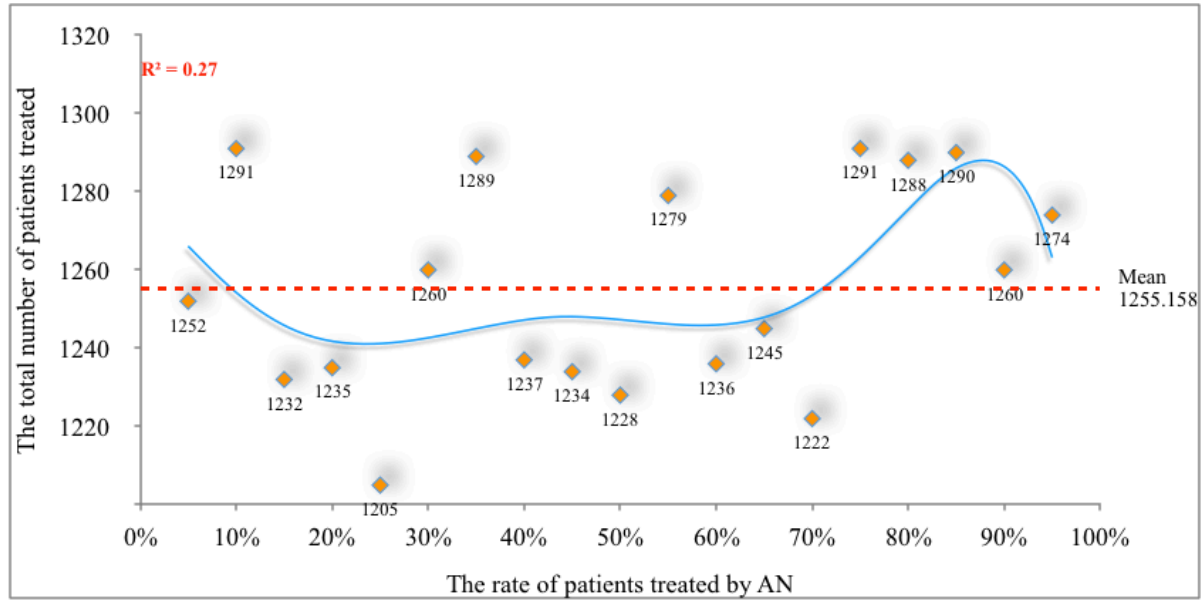


Figure 44: The effect on the number of patients treated by HSN based on 7/24

The relationship between the length of stay and the rate of patients treated by AN is shown in Figure 44. The rate of patients treated by AN showed a fourth-degree polynomial distribution with an increase and the length of stay in ESs decreased inversely. The average length of stay was computed as 54.192 minutes, which means a 34.28% improvement was reached. The mathematical formula of the length of stay is given as:

$$y_{los}^{7/24} = 0.0151x^4 - 0.7716x^3 + 14.019x^2 - 106.63x + 325.81 \quad (71)$$

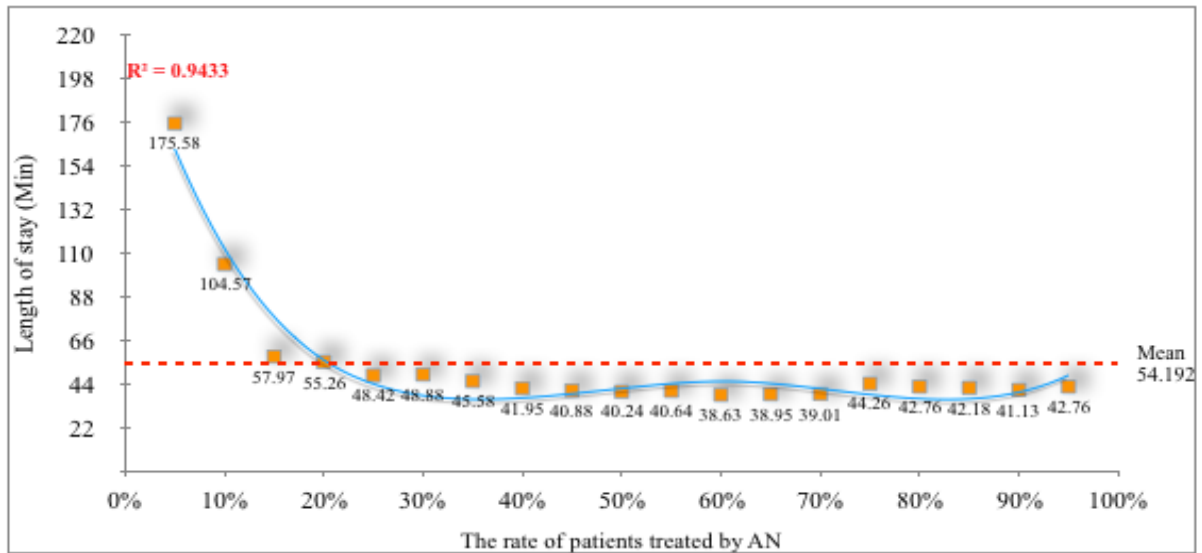


Figure 45: The effect of the rate of patient treated by HSN on the LOS based on 7/24

Figure 46 shows the efficiency rates of the existing resources of ES. The utilization of physicians and exam rooms decreased with an increased rate of patients treated by AN. The reason behind the escalation of triage units' intensity is the utilization of triage units as exam rooms or beds for patients treated by AN.

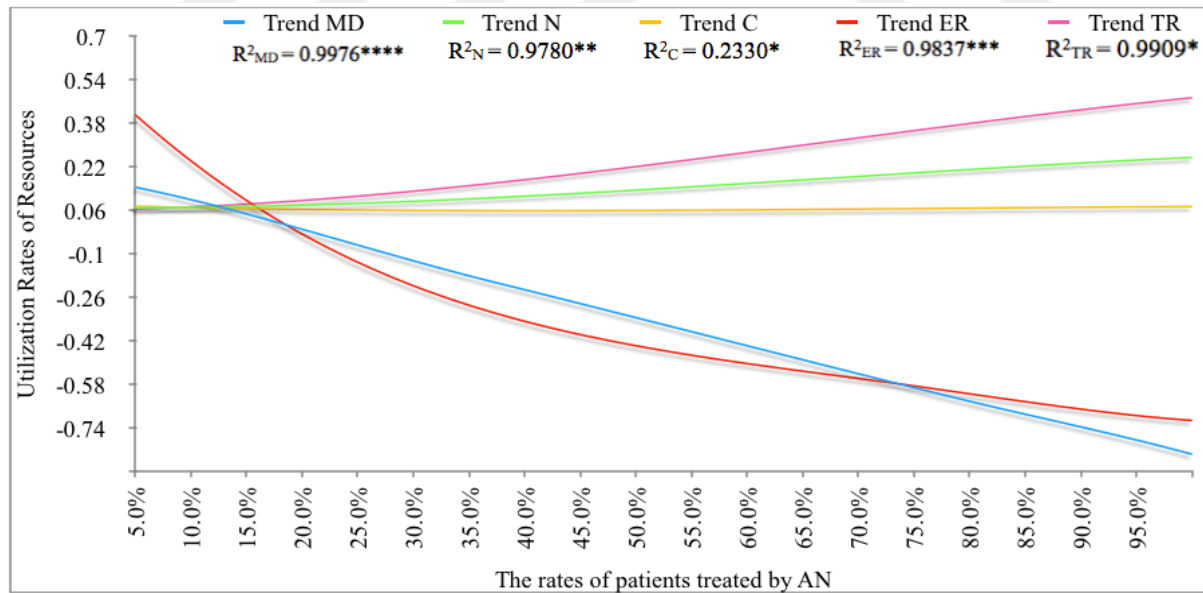


Figure 46: Effect of YUH employment on resources based on 7/24

Note: *, **, *** and **** were expressed as third-, fourth-, fifth- and sixth-degree nonlinear curves with high R^2 , respectively.

When the results that were obtained from the scenarios of the simulation models were compared, it was seen that AN employment increased the satisfaction of patients and made the resources more efficient. In Table 48 and Table 49, data on the simulation models are given in detail. According to these data, changes were observed in the patient waiting times, length of stay in ES, and in the number of patients treated. Similarly, it is seen that changes in the efficiency of the resources used for the simulation model are positive.

The data in these tables were obtained from the 19 scenarios (with AN) and 1 scenario (without AN) that was produced for the first and second situation of the simulation model. In this study, the results of the scenarios were determined as percentage changes. The percentage of patients who were treated when ANs were employed was simulated between 5% and 95% with 5% intervals. There were differences in the rates of the patients who arrived at ES but did not have any urgent conditions. For this reason, 19 scenarios were formed, data were obtained for every possible condition, and the average was considered. However, according to the literature data, the rate of patients who do not have any urgent situations, but nonetheless apply to ESs, is generally above 50%. When this rate is considered, it is the level in which the patient waiting rates were at the lowest level in the simulation results obtained on a 1/24 basis. The lowest level (D) was obtained with a ratio of 40%/60% (AN) on a 7/24 basis.

It was observed that there was an imbalance in the efficiency rates of the resources that were employed in the ES. As the rate of the number of patients who are treated after ANs changed, it was observed that the resources with unbalanced efficiency rates became more balanced. It was ensured that the productivity of the doctor resource, which was difficult to employ, was reduced and the need for the number of doctors employed number was decreased.

We conclude that the results of the parameters determined are more realistic than the findings of previous studies. The fact that the results obtained in studies using different methods are based on observations and that the findings obtained in this study are based on numerical results supports the accuracy of the findings. As compared to the findings of other studies, we argue that the waiting time (mean time 45.6 minutes vs. 20.69 minutes) and length of stay (mean time 107.2 minutes vs. 53.88 minutes) decreased more.

2.4. Conclusion

The main purpose of this study was to solve the intensity problems in ESs of Turkey. This research recommended that advanced nurses be employed in a more active way by determining their skills and authorities. The aim of this recommendation was to reduce the intensity in ESs so as to reduce the waiting times and length of stays of patients, which are the most important indicators of patient satisfaction.

The use of discrete event computer simulation provided the results of the parameters defined in the research. The reason for the application of simulation models, which were performed by imitating real systems, was their ability to yield tangible, consistent and valid results. The strategies or scenarios, which are expected to be realized in daily life, require high costs and longer times. However, with the help of simulation, it was ensured that the results of the strategies and scenarios were obtained in a cost-efficient way and a short time.

In the present study, a 3D simulation model was developed for two situations in an ES of Turkey. The number of the patients treated, waiting times of the patients, length of stays, and utilization of the resources of ES were compared within each scenario. The findings demonstrate that the number of patients treated increased at a rate of 26.71% on a 1/24 basis, and 15.13% on a 7/24 basis, by providing AN employment. From the moment patients are referred to the ES, the waiting time for treatment was reduced to 20.58 minutes from 33.24 minutes on a 1/24 basis, and from 44.89 minutes to 20.80 minutes on 7/24 basis. This means that improvements of 38.09% and 53.66% were achieved, respectively. Another finding of the study was that the length of stay (from registry to discharge) decreased by an average of 28.49 minutes in the ES. The last finding is related to the appropriate management of the healthcare institution, including the utilization of the resources it has. Generally, the efficiency achieved by the resources is too high or low (unbalanced efficiency rates) in ESs. In the context of the results, it was observed that balance was achieved in the efficiency rates of the resources with the employment of AN.

Briefly, as a result of the inability to use triage units in an accurate manner, disruptions and intensive workloads are observed in the functioning of ESs in Turkey (after the admittance of a patient in ESs, the unit that will guide the patient and the resources is known as the triage unit). In the current situation, triage units provide only information on the area where the

diagnosis and examination of the patient will be made. There are no examinations or treatment procedures in these units. We advocate running triage units in a more active way with the employment of ANs in this study.

As a result, the employment of ANs in ESs must be considered by the government in the healthcare system of Turkey. This recommendation contributes to the decrease of the intensities in ESs and the employment of resources in a more efficient and effective manner.



Chapter 3: Development of an Optimization Model to Generate the Hospital Competitiveness Index

3.1. Introduction to Hospital Competitiveness Index

The perspective towards the importance of the healthcare has changed in a severe way from the past to the present. Two of the main reasons for this are people's desire to live long and the increasing perception of healthcare area as a business sector. Globally, healthcare is the second largest sector after manufacturing in an economical manner. This situation is triggering the development and growth of the healthcare sector (Gowen, McFadden, & Tallon, 2006). Healthcare institutions establish a competitive atmosphere for patients to receive faster and easier health services.

Accordingly, as the level of welfare in people increases, they demand the high quality of healthcare they receive services from the healthcare institutions. All of these are particularly inspiring quality in healthcare systems to increase. It is desirable for people to have high patient satisfaction by receiving high quality services in easy and fast way from health institutions. Especially in European countries, people travel to other cities or countries because of long waiting time and poor-quality health services in the city where the patients are located.

Many methods have been developed to solve these healthcare problems. However, since health problems are very specific problems, researchers have adopted algorithms and optimization models (Andritsos & Tang, 2014). Optimization technique are generally indispensable methods of management, engineering, and business applications. The purpose of using optimization, also named as operation research (OR), is to provide maximum benefits (such as revenue, production, etc.) and minimize loss (such as costs, waiting time, etc.). Optimization applications vary widely according to the areas where they are used, such as energy, automotive, manufacturing, transportation, logistic. Optimization techniques have been exploited to solve probes in healthcare systems, which are among the most trend topics of recent years. Commonly, optimization models have been developed to optimize the schedule of resources of the healthcare systems (Mehroolhasani, Mouseli, Vali, & Mastaneh4, 2017). In addition, optimization models have been developed for the management of healthcare materials for logistics (Visser & Beech, 2005), for emergency services, to reduce waiting time for patients (Ahmed & Alkhamis, 2009; Cabrera, Taboada, Iglesias, Epelde, & Luque, 2011), and

to reduce expenditure on healthcare facilities (Iii et al., 2001). However, this method has been used limitedly in the field of healthcare. The reason for this is that work flows in the healthcare system have a rather stochastic structure rather than a deterministic structure. Stochastic constructions are usually explained by nonlinear equations that means the analysis of mathematical modeling is both difficult and long-lasting in parabolic situations.

Statistical analysis is an alternative method for solving healthcare problems (Malehi, Pourmoghari, & Angali, 2015). In particular, statistical methods have been used to make predictions for healthcare system management in the future based on past data and experience. Especially, regression analysis was used among statistical methods by researchers (Gregori et al., 2011; Montgomery, Peck, & Vining, 2012). For this reason, regression analyses are considered as a good forecasting tool for the future. However, it is not sufficient to use solutions alone in healthcare area, because of the fact that the statistical analysis obtained provides only information about what the current system will achieve in the future, not the future goals of these systems. For this reason, statistical analysis is used together with optimization technique in this study. In addition to statistical analysis, calculation of GHCI values belonging to countries is provided by using desirability technique. A formula is obtained by considering the lower and upper limits of the factors considered on the basis of this technique. With this method, it is possible to clearly show the traces of the factors on which they affect the response which is the objective function of the optimization model.

It is seen in the previous studies that the researchers have just paid attention to the index of urban competitiveness (UCI) (Kresl & Singh, 2012; Lever & Turok, 1999; N. Pengfei & Kresl, 2014; Ni Pengfei & Qinghu, 2017; Sáez & Periañez, 2015; Viorica, 2000). Those studies have mainly covered the economic characteristics besides the social and infrastructural factors of the urbans (Bruneckiene, Guzavicius, & Cincikaite, 2010). Urbans with high UCI values have the power to compete more than other cities in terms of economy and they are perceived as attractive centers for business. Another subject related with competitiveness index is the calculation of global manufacturing competitiveness index that takes into account how high production capacity is achieved (Gif, Rodriguez, Gangula, Roth, & Hanley, 2016).

An optimization model with the help of statistical analysis was developed to create GHCI to measure the structural and economic status of healthcare of considered countries in the light of earlier competitiveness index studies for this study. It also demonstrates the quality of the health

systems that GHCI countries have. Up till now, the quality of healthcare has only been determined on the basis of patient satisfaction (Dansky & Miles, 1997; Kamra, Singh, & De, 2015; Naidu, 2009). This criterion is measured according to surveys, so the numerical data and analysis are disregarded in the researches' studies. Patient satisfaction and employee performance were measured using questionnaire or verbal interview method to determine the quality of healthcare (Marsh, Lanitis, Neasham, Orfanos, & Caro, 2014). However, it is obvious that the results of such methods are weak in terms of accuracy or not enough to reflect the real the problems of healthcare. For this reason, different methods have to be used to obtain quantitative and tangible results. Through this research, the results of the analysis with the numerical data by quality tools have led to touchable solutions for quality of the healthcare and allowed the detection of the future problems. We believe that this study will be a good source for future studies in terms of measuring method of the healthcare quality.

This section of the thesis has come to fruition in four parts. In the first section, the studies in the literature have been discussed. The methodology of the study is taken into account in the second section. The factors affecting the healthcare systems are determined and methodologies of the study are constructed on this part. In the third chapter, statistical and optimum results were obtained with the developed method for GHCI and the GHCI values belonging to the countries were calculated. In the last section, conclusion about the study has been provided.

3.2. Factors of the GHCI and Collection of Related Data

The factors affecting healthcare systems were evaluated in two parts which are defined as structural and economical. The factors come from the resources that build the substructure of the healthcare system in the first part. Some of these factors are: doctors, assistant doctors, nurses, officers, patient rooms, beds, triage rooms, laboratories fulfillments of clinical requirements, general behavior of doctors, registration and administrative procedures, infrastructure and amenities, professional performance of doctors and facilities at reception and out-patient department area (Kamra et al., 2015)(Donoghue et al., 2006). These resources must be supplied and managed properly in a healthcare system. Nevertheless, deficiencies in the management of these resources are affecting the quality of healthcare in the negative direction (Rowe, de Savigny, Lanata, & Victora, 2005). General believing, physicians, nurses and beds construct the infrastructure of the healthcare systems. Thus, the numbers of physicians, nurses, and beds (OECD, 2017) that are used in this study are the most employed parameters in the researches.

The resources of the healthcare system of the countries were calculated by the world database as the number of beds, doctors, and nurses per 1000 persons. However, in order for the analysis of these data to be consistent, the total number of these sources is calculated as below:

$$\sum x_{ji} = \sum [x(\text{per 1000 people})_{ji} * \frac{\text{Population}_{ji}}{1000}] \quad (72)$$

where; i represents the names of the countries, j denotes the resources of healthcare of the countries, $j = (\text{beds, physicians, and nurses and midwives})$.

The life expectancy (World Population Review, 2017) factor discussed is also considered among the structural factors in this study. Especially, this factor may be more effective in state and private healthcare systems. The main reason for this deal is that people with high levels of prosperity are increasing their healthcare expenditures because people want to live longer. In this case, states or private enterprises need to increase their healthcare expenditures.

In terms of economy, there are many factors that are influential in the healthcare system levelheadedly. Before the determination of the economic factors of the GHCI, it is necessary to examine the healthcare systems worldwide. There are two types of healthcare systems around the world which are private and state healthcare systems (Zerda et al., 2002). It is seen that social healthcare systems have more healthcare expenditure than non-social healthcare systems. Though, private healthcare systems have developed in non-social states such as the U.S. healthcare system. The reason for this is that most of the healthcare expenditures are covered by patients or those with healthcare insurance in these countries. Healthcare expenditures are considered as response or independent factors influenced by factors. We employed the healthcare expenditure as one of the predictors because the quality of healthcare used to be more valid by governments (Farahani, Subramanian, & Canning, 2010; Filmer & Pritchett, 1999; Kumar et al., 2011; Rajkumar & Swaroop, 2008; Xia, Liang, Zhang, & Wu, 2012).

There are two economic factors that are gross domestic product (GDP) (OECD, 2016) and gross domestic product per capita (GDP PC) (WBG, 2017). Countries with GDP PC of \$10,000 or more are regarded in this study. Additionally, GDP of the well-thought-out countries considered to be influential on the healthcare systems were also included. It is thought by researchers that countries with high GDP allocate more budget for healthcare systems. Most of studies covered at most six and few factors in the calculation of index scores. Generally, scientists suggested that the four independent variables are effective and reliable (Shane, 1993). In this study, many indicators were mentioned under six main factors.

Healthcare expenditure data of countries (OECD, 2016) are calculated by the percentages of countries dependent on GDP (World Bank, 2014) (Equation 2). A statistical analysis of how these factors affect health expenditure has been shown to result.

$$Health\ Expenditure_i = [Total\ GDP_i * Health\ Expenditure(\% \ of\ GDP)_i] \quad (73)$$

where, i represents the names of the countries.

Healthcare expenditure of countries are considered as a response variable. As a general opinion, as people's quality of life and their willingness to live increases, health expenditure also increases. As such, it is inevitable that improved health systems will be formed with a good infrastructure. But all of this requires cost. It is seen that health expenditures in economically developed countries are higher than developing countries. As a result of the statistical analysis,

which of the seven important factors considered in this study is more influential on health expenditures is revealed. An optimization model was developed with the mathematical equation of the developed regression. This model is provided to minimize the amount of healthcare expenditure besides of maximization of GHCI which the objective function is.



3.3. Development of Optimization Model for GHCI

The desirability analysis and optimization techniques have been merged to create the main methodology of this study. In order to construct the optimization model, the regression equation obtained as a result of statistical analysis and the GHCI values belonging to the countries are calculated.

The method of desirability has been developed to obtain the best results for multiple reactions or factors acting as a process. For this reason, it produces the best response values of the factors to minimize, maximize, or reach the target value of the specifications. While statistical analysis gives mostly linear regression equations, the equilibrium found due to the weighted factor values in the desirability technique has a nonlinear characteristic.

Before constructing the optimization models, it is necessary to consider the function of desirability according to the results to be obtained as a result of statistical analysis. The factors affecting the response function directly influence the desirability function (Wu, 2004). In short, it is desirable that the factors affecting the main response values are at the target values which are measured by the value of desirability. The best result is gained as this value goes from zero to one. When calculating the desirability;

To find n factors' values and the function of each response value is expressed as;

$$y_i = f_i(x_1, x_2, \dots, x_k), i = 1, 2, \dots, n \quad (74)$$

The desirability function is specified as;

$$d_i = d_i(y_i) = d_i(y_i(x)) \quad (75)$$

$d(y)$ takes a value between 0 and 1. If $d_i(y_i) = 1$, this is the desired best value (Hu, Cai, & Han-HuaLiang, 2008; R.Costa, Lourenço, & L.Pereira, 2011), but if $d_i(y_i) = 0$, it is the worst and undesirable value.

General desirability is expressed as follows;

$$d_i(y_i) = \left(\frac{y_i - l_i}{u_i - l_i}\right)^{w_i}, l_i \leq y_i \leq u_i \quad (76)$$

where l_i and u_i are the lower and upper specification limit, and w_i is higher than other weighted factors, how important the role of $d_i(y_i)$ in overall desirable is. There are three purposes for the value of desirability. These are maximum, minimum and target values in the objective functions. However, there are three different conditions for each of these three situations.

- For maximization problems, the desirability function;

$$d^{max} = \begin{cases} 0, & \text{if } y_i \leq l \\ \left(\frac{y_i - l}{u - l}\right)^{w_i}, & \text{if } y_i \leq u, y_i \geq l \\ 1, & \text{if } y_i \geq u \end{cases} \quad (77)$$

- For minimization problems, the desirability function;

$$d^{min} = \begin{cases} 0, & \text{if } y_i \geq u \\ \left(\frac{u - y_i}{u - l}\right)^{w_i}, & \text{if } y_i \leq u, y_i \geq l \\ 1, & \text{if } y_i \leq l \end{cases} \quad (78)$$

- For target, the desirability function;

$$d^{target} = \begin{cases} \left(\frac{y_i - l}{u - l}\right)^{w_i}, & \text{if } y_i \leq u, y_i \geq l \\ \left(\frac{u - y_i}{u - l}\right)^{w_i}, & \text{if } y_i \leq u, y_i \geq l \\ 0, & \text{if } y_i \leq l \text{ and } y_i \geq u \end{cases} \quad (79)$$

The closed desirability function equation to be obtained by considering these three conditions is calculated by the geometric mean (see equation 80).

$$D^* = (d_1 * d_2 * d_3 * \dots * d_n)^{1/n} \quad (80)$$

The complete desirability function includes the upper and lower bound values of the factors that have an effect on the responses. GHCI was created separately for each factor. GHCI formula was obtained by geometric mean of these factors. However, the values of GHCI and

HE are converted to the following formula in order to get a meaningful and normal result. Thus, the value of GHCI and HE are not placed between 0 and 1, so that they take a value between 0 and depending on c.

$$[1 - D^*] * c = [1 - (d_1 * d_2 * d_3 * ... * d_n)^{1/n}] * c \quad (81)$$

There are seven different factors in this research, and the expansion of these factors on the desirability formula is shown as below:

$$GHCI_i = [1 - \left(\frac{y_1 - l_1}{u_1 - l_1}\right)^{w_1} * \left(\frac{y_2 - l_2}{u_2 - l_2}\right)^{w_2} * \left(\frac{y_3 - l_3}{u_3 - l_3}\right)^{w_3} * \left(\frac{y_4 - l_4}{u_4 - l_4}\right)^{w_4} * \left(\frac{y_5 - l_5}{u_5 - l_5}\right)^{w_5} * \left(\frac{y_6 - l_6}{u_6 - l_6}\right)^{w_6}]^{1/6} * c \quad (82)$$

$$HE_i = [1 - \left(\frac{u_1 - y_1}{u_1 - l_1}\right)^{w_1} * \left(\frac{u_2 - y_2}{u_2 - l_2}\right)^{w_2} * \left(\frac{u_3 - y_3}{u_3 - l_3}\right)^{w_3} * \left(\frac{u_4 - y_4}{u_4 - l_4}\right)^{w_4} * \left(\frac{u_5 - y_5}{u_5 - l_5}\right)^{w_5} * \left(\frac{u_6 - y_6}{u_6 - l_6}\right)^{w_6}]^{1/6} * c \quad (83)$$

where; c is a multiplier that is used to have the result obtained have normal values in above equation. The optimization model was obtained by considering the factors affecting GHCI and HE (see Table 44). The following developed equation has been used as an objective function with the constraints to determine the competitiveness indexes of a country which are used in this study.

Factors' variables were abbreviated as gross domestic product, *GDP*; gross domestic product per capita, *GDP PC*; life expectancy, *LE*; the number of beds, *B*; the number of nurses and midwives, *NW*; the number of physicians, *MD*.

Table 44: Descriptions of the Optimization Model's Rudiments

Types	Notations	Definitions	Boundaries
Decision Variables	x_{ij}^y	The amount of the types of factor i , the country of j during the year y	$i = \{p, gdp, gdp\ pc, le, b, p, nw\}$ $j = \{Norway, \dots, Costa\ Rica\}$
Parameters	l_{ij}^y	The lower bounds factor i the country of j during the year y	$\forall_y \in \Omega$
	u_{ij}^y	The upper bounds factor i the country of j during the year y	$\forall_y \in \Omega$
	β_i	Normalization multiplier for factor i	$i = \{p, gdp, gdp\ pc, le, b, p, nw\}$
	n_y	Total numbers of years	$\forall_y \in \Omega$
Objective Functions	$\sum_{i,j} \sum_y GHCI_{ij}^y$	GHCI for factor i the country of j in the year y	$\forall_y \in \Omega$
	$\sum_{i,j} \sum_y HE_{ij}^y$	GHCI for factor i the country of j in the year y	$\forall_y \in \Omega$

$$\text{Maximize } \sum_{i,j} \sum_y GHCI_{ij}^y \quad (84)$$

$$\text{Minimize } \sum_{i,j} \sum_y HE_{ij}^y \quad (85)$$

Subject to

$$\sum_{i,j,y} x_{ij}^y \beta_c \geq \sum_{i,j,y} \frac{l_{ij}^y}{n_y} \quad (86)$$

$$\sum_{i,j,y} x_{ij}^y \beta_c \leq \sum_{i,j,y} \frac{u_{ij}^y}{n_y} \quad (87)$$

$$x_{ij} \geq 0 \quad (88)$$

The upper and lower bound values in the form for the desirability value are shown in the

Figure 47. There are two cases in evaluating the upper and lower bounds in the GHCI formula. When the upper bound value is examined (0-8000), it is seen to be the effect of the values in the range. (8000-infinite) values were not found to have any effect on GHCI. Lower bound values (0-2000) have no effect on GHCI, but (2000-infinite) values show the effect. The variability in these values is valid only for one factor, which also represents constraint, to reflect the effect on the objective function.

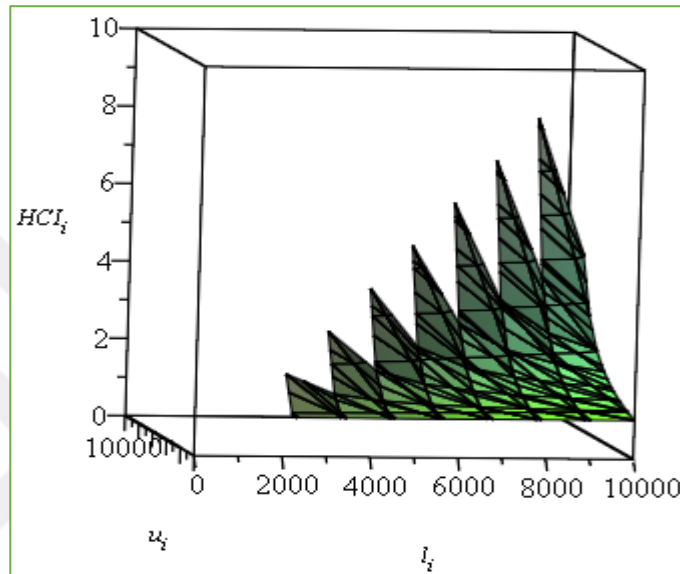


Figure 47: Effect of upper and lower bound values on Global Healthcare Competitiveness Index (GHCI)

3.4. Results of Statistical Analysis of GHCI's Factors

This section provides general information about the collected data for statistical analysis and shows the accuracy of the analysis. The precision of the factors with the effects on the response is measured. The results of statistical analysis show that the accuracy of the collected values have high R-values. The accuracy of the statistical analysis of this study was 99.68% of the R^2 value and 99.63% of the adjusted R^2 value.

The effects of the determined factors on the GHCI were examined. The importance of a factor on the response depends on the *p-value* of the factor as a result of the statistical analysis. In the 95% confidence interval, if the p-value is less than 0.05, this factor is important for the response. Contribution ratios are calculated as percentage of contributions to the total sequential *SS* of each source in the tables of variance analysis. Higher percentages of contributions rates indicate that more variation on the response is calculated.

Table 45: Statistical results of the independent and dependent variables

Category	Source	Contribution	95% CI	P-Value	Status
	Model	99.98%	(-1.9731; -1.9231)	0.0000	Significant
Economical	GDP PC	4.98%	(-0.011575; -0.011412)	0.0001*	Significant
Economical	GDP	17.20%	(0.000037; 0.000037)	0.0001*	Significant
Economical	Healthcare Expenditure	32.23%	(0.000401; 0.000170)	0.0714**	Prov. Significant
Structural	Life Expectancy	32.23%	(0.040874; 0.041548)	0.0001*	Significant
Structural	Beds	2.34%	(-0.018633; -0.017805)	0.0001*	Significant
Structural	Medical Doctors	7.54%	(0.009801; 0.011563)	0.0001*	Significant
Structural	Nurses and Midwives	35.69%	(0.055349; 0.056119)	0.0001*	Significant

Note: to determine the individual effects of the factors that could affect the response and

*statistically significant (p-value < 0.01),

**at the margin of statistical provisionally significance (p-value < 0.1)

Contribution: displays the percentage that each source contributes to the total variation in the response.

CI: Confidence Interval is an interval estimation type for the actual values of an unknown population parameter calculated from the statistics of the observed data.

P-Value: The p-value is a probability that measures the evidence against the null hypothesis

The statistical analysis is illustrated in Table 45. The most important factor is found as GDP by country in the statistical analysis (*p-value of GDP is almost zero*). Among other factors; GDP PC, nurses, and beds impress strongly the healthcare expenditure and GHCI. However, these results indicate that GHCI are not influenced by the health expenditure, of a country. Thus, this factor is excluded in the application optimization model to calculate optimum values of remained factors, is defined as an objective function. Note that the effects of factors considered for GHCI are measured as non-interactively.

3.5. Calculation of Optimum Values for GHCI

Optimization mathematical model for optimizing both the factors and the objective function (or response) was developed. These values show the necessary data to compete for a country in the field of healthcare. Considering the factors, it is analyzed that the calculated values are higher than the mean of the data of 53 countries. As a result of the statistical analysis, it is revealed which of the six out important factors discussed in this study is more effective on health expenditures and GHCI. Figure 48 shows the variation of the feasible results obtained for GHCI and HE according to D^* . The optimum point is located between 0.64 and 0.66 of D^* shown in the figure. The optimal point is to be within the feasible area, but two different objective functions (for different directions: max-min) ensure that the solution is nonlinear.

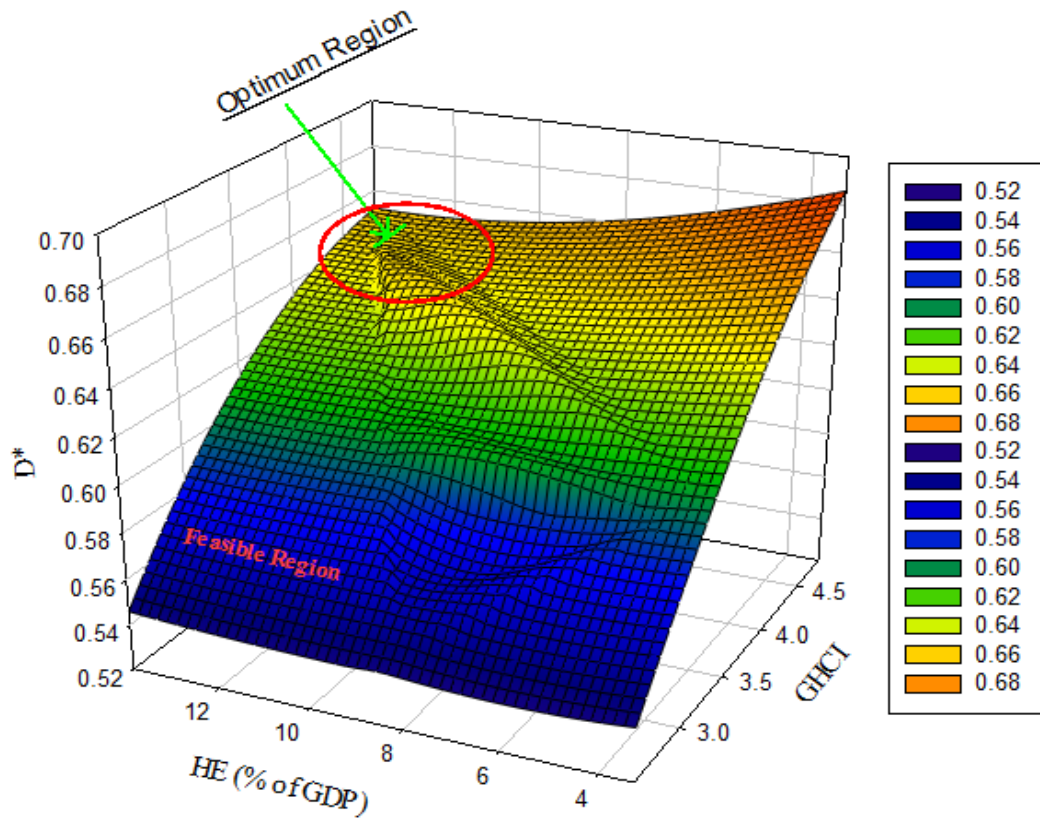


Figure 48: Optimal point according to D^* , GHCI, and HE

In the context of the investigations, as people's quality of life and their willingness to live increases, health expenditures increase. In terms of the data, it is seen that health expenditures are high in economically developed countries. When the healthcare policies of governments are examined, it is desirable to reduce the healthcare expenditure which is a burden on the country economy. Table 46 demonstrates that the objective function and the factors

constituting the constraints have optimum and feasible values.

Table 46: Optimum and feasible values of GHCI and HE

Optimality Setting	Decision Variables						Objective Functions		Status
D*	GDP (Billion \$)	GDP PC	LE	B (per 1000)	MD (per 1000)	NW (per 1000)	GHCI Score	HE (% of GDP)	
0.6520	\$776.77	\$44.96	80.16	7.62	4.77	13.24	4.8155	13.96	Optimum
0.6481	\$751.42	\$46.91	81.28	8.66	6.26	12.52	4.4967	13.14	Feasible
0.6433	\$548.58	\$35.20	80.91	10.04	5.13	10.83	4.0470	11.91	Feasible
0.6127	\$777.76	\$45.94	81.29	6.77	4.84	8.90	3.5266	10.65	Feasible
0.6034	\$751.42	\$46.91	76.40	7.29	5.13	12.28	3.2886	3.29	Feasible
0.6006	\$877.18	\$45.94	79.78	10.04	4.55	9.63	3.2478	9.94	Feasible
0.5917	\$776.78	\$45.94	81.28	10.90	5.42	8.90	3.1211	9.67	Feasible
0.5710	\$954.26	\$51.80	76.78	7.63	4.84	10.59	2.8988	9.05	Feasible
0.5548	\$878.20	\$55.70	79.79	10.04	4.54	9.62	2.6377	8.47	Feasible
0.5503	\$878.19	\$54.72	79.99	12.80	4.04	10.11	2.5886	8.36	Feasible
0.5427	\$777.76	\$45.94	76.78	6.77	4.84	8.90	2.5047	8.14	Feasible

By examining the optimum values of the factors, it is necessary that the budget rate that should be used for minimizing the health expenditures and maximizing GHCI of the selected countries to measure the power of competitiveness in terms of healthcare systems.

In the same way, when the optimum values of the factors in the infrastructure of the healthcare systems are considered, the number of medical doctors and beds are striking. As a result of the statistical optimization analysis that these factors have a lot of influence on GHCI and HE. With these results, an increase of 38.15% for the number of nurses and midwives (the average number of nurses and midwives was 7.5930 per 1000 people) and 41.18% for the number of beds (the average number of beds was 4.2850 per 1000 people) in a country's healthcare system is required. In the same manner, countries need to employ 42.75% more for doctors (the average number of nurses was 2.9350 per 1000 people) (see Figure 49).

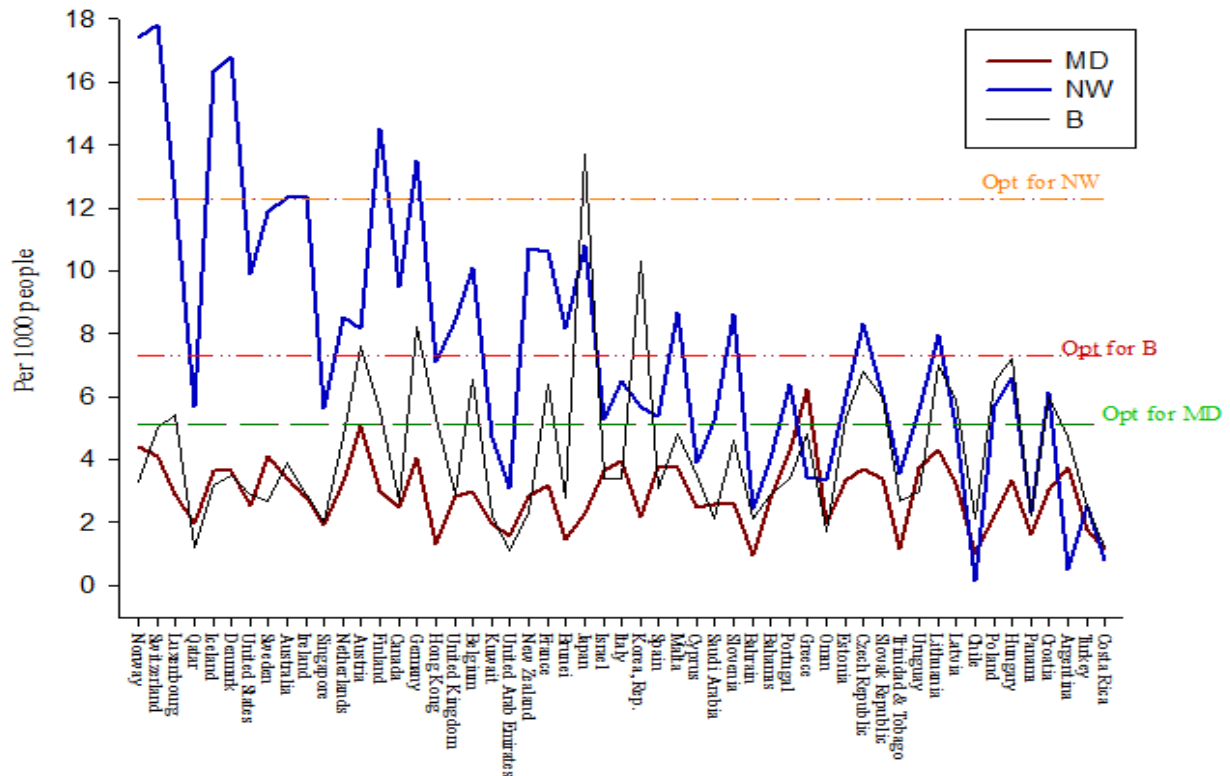
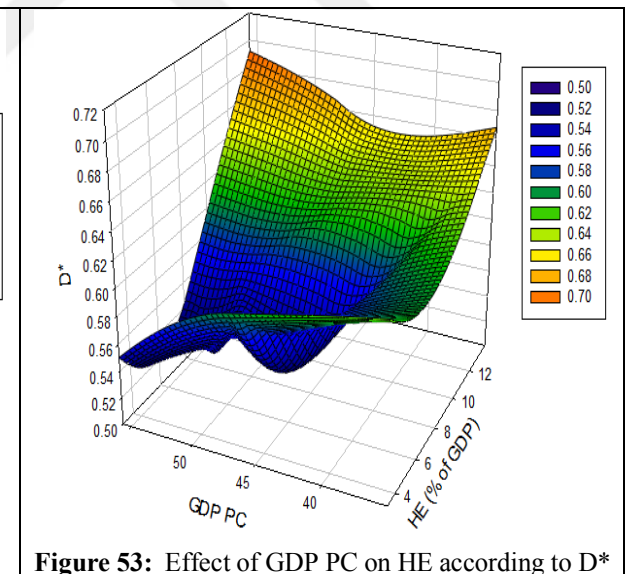
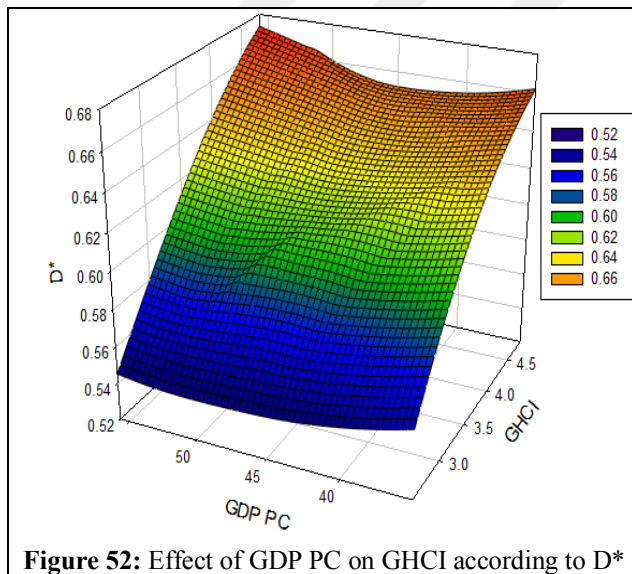
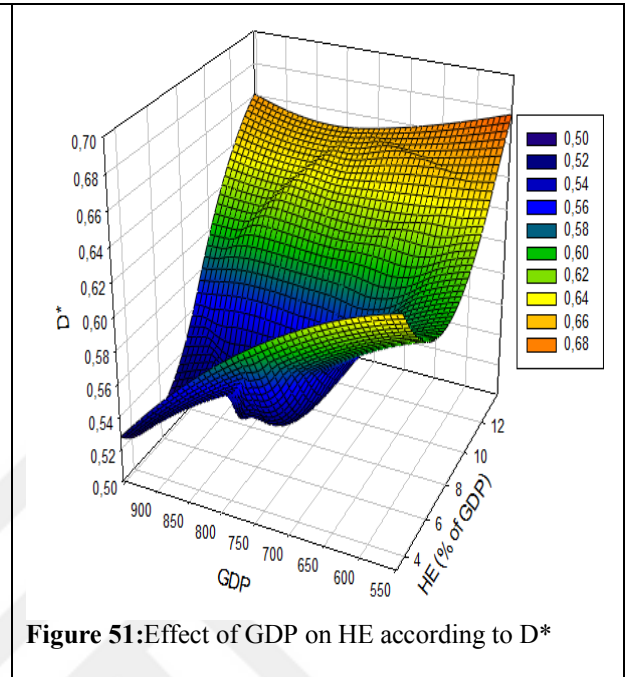
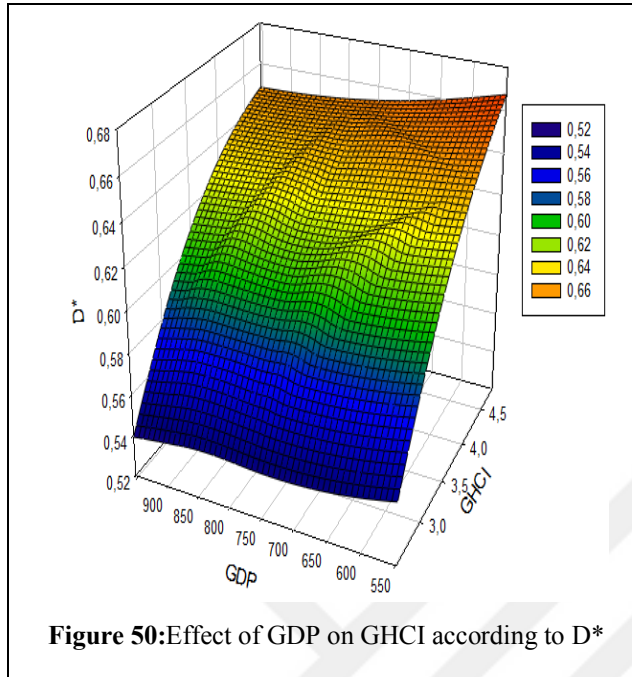


Figure 49: The numbers of the resources of healthcare systems of countries according to optimum values

The values that each factor takes outside of optimum values are seen to affect the objective function either in the positive or negative direction. As GDP and GDP PC values of the factors increases, the value of the objective function increases too. On the reverse side, the values of the number of beds increase from the factors, the value of the objective function decreases. It can be mentioned GDP and GDP per capita are positive for the health system of the country with the increase in Life Expectancy values as well as negative effects on the healthcare system of a country. In terms of the resources of healthcare the GHCI value increases with a certain increase in the number of doctors, nurses and midwives without the number of beds. However, the numerical increase of these resources reaching a certain number does not affect the value of GHCI and HE as well. Generally speaking, countries need to pay attention to resource management of healthcare system that matches our findings in this study.

Figure 50, Figure 51, Figure 52, Figure 53, Figure 54, Figure 55, Figure 56, Figure 57, Figure 58, Figure 59, Figure 60, Figure 61 show the effect of the factors affecting the healthcare system on GHCI and HE. The calculation of the optimum values for each factor was completed by considering the D* value. The most important point to be considered in these figures is that the factors that

are effective in the healthcare system have the maximum values for the GHCI value (local maximum), forcing it to be at a minimum level (local minimum) for HE.



It has two different behaviors in order to get the optimum values of the factors. While the factors want to get the maximum value for GHCI, they want to get the minimum values for HE. Therefore, D^* values have different range for each figure. Although HE and GHCI are defined as two independent objective functions, GHCI is affected by HE. Our findings infer that HE should continue to improve GHCI so that GHCI can become a much better forecaster of the quality of healthcare.

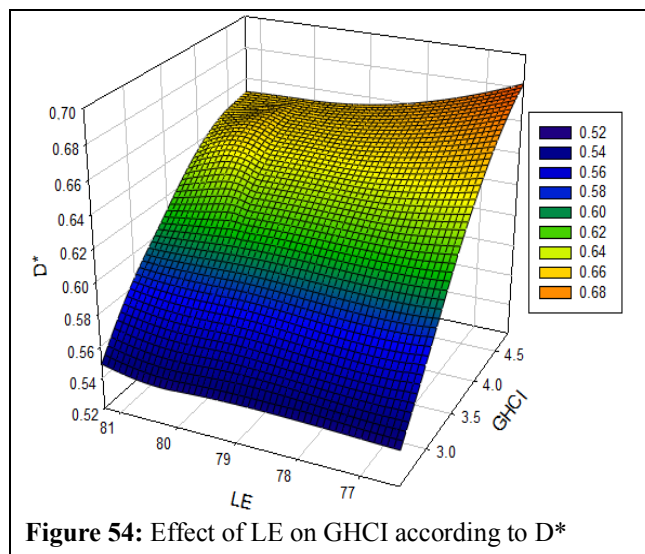


Figure 54: Effect of LE on GHCI according to D*

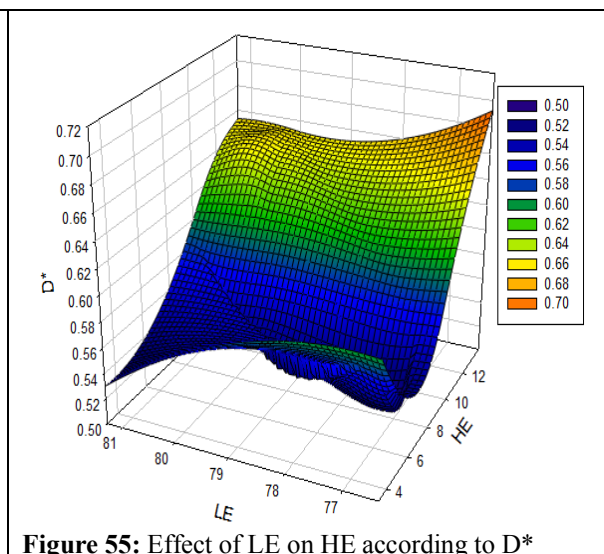


Figure 55: Effect of LE on HE according to D*

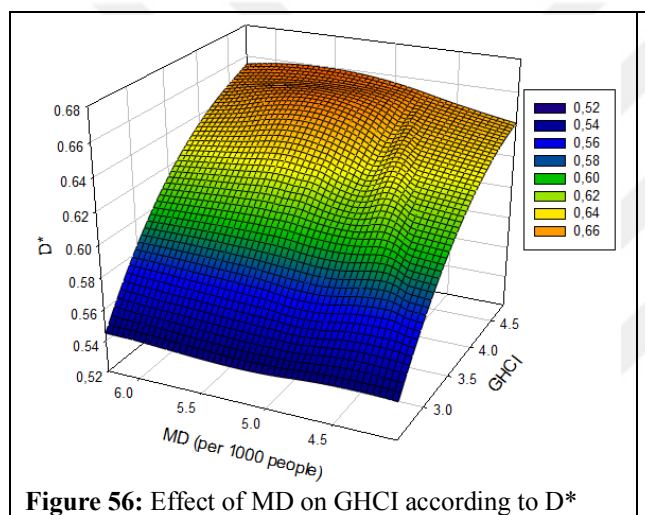


Figure 56: Effect of MD on GHCI according to D*

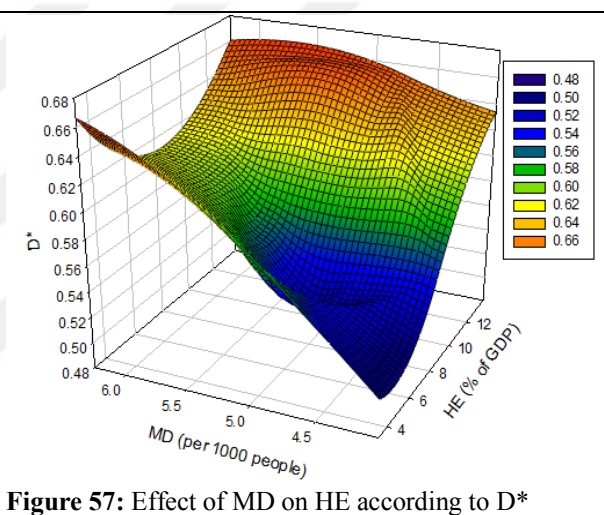


Figure 57: Effect of MD on HE according to D*

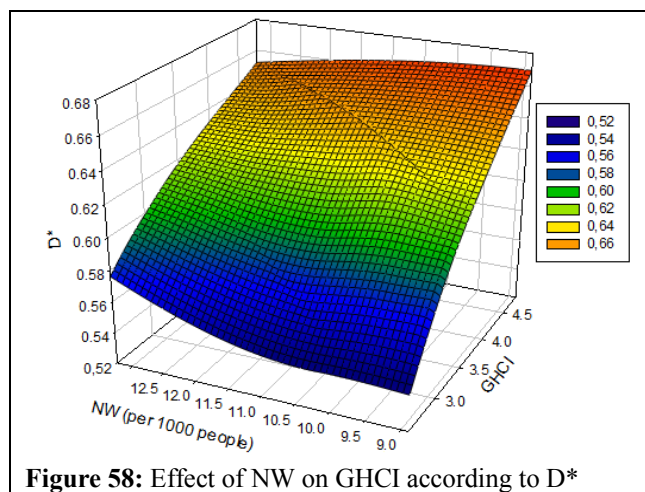


Figure 58: Effect of NW on GHCI according to D*

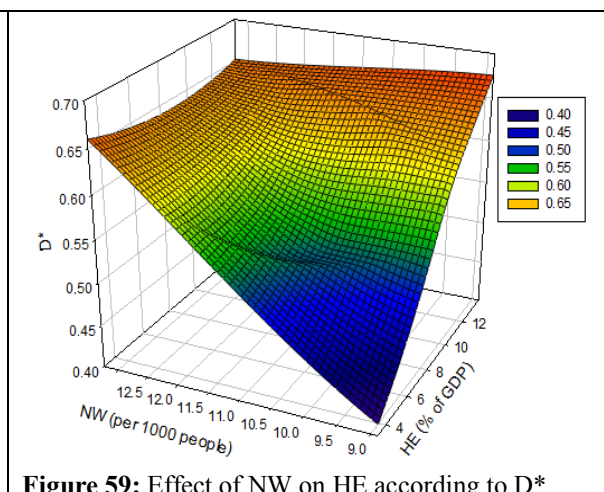


Figure 59: Effect of NW on HE according to D*

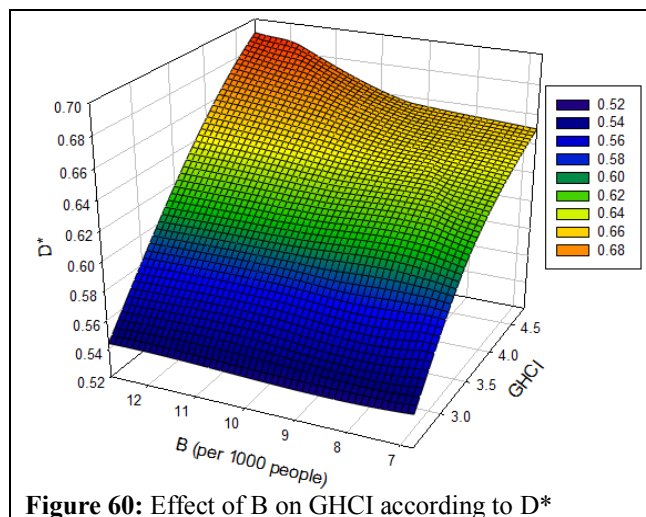


Figure 60: Effect of B on GHCI according to D^*

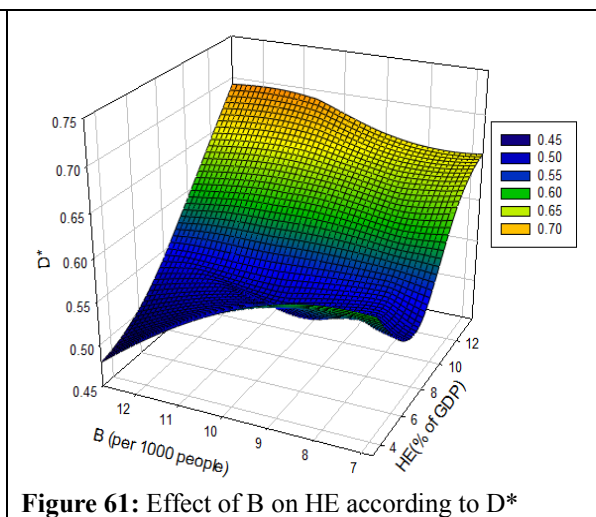


Figure 61: Effect of B on HE according to D^*

3.6. Generating the Global Healthcare Competitiveness Index

The optimization model with statistical analysis has been developed to demonstrate the competitiveness of the healthcare systems of the countries covered in this study. Previously, the country ranking was made by the amount of GDP PC. However, with this study on healthcare, country rankings were made by calculating the GHCI scores of the countries. A country with a high GHCI score in this order has a quality and competitive healthcare system. Such healthcare systems will have the ability to offer a better service to the patients. The GHCI scores of the countries ranged from 0 to 6. The average of the GHCI values of the countries is 2.4758. When the GHCI scores were examined, it was found that the highest value was in the United States (5.7490) and the lowest value was in Qatar (0.4301) (see Table 47).

Table 47: GHCI Scores and Ranking

GDP PC Rank	Country	GHCI Score	GHCI Rank	GDP PC Rank	Country	GHCI Score	GHCI Rank
1	Norway	2.7898	20	28	Korea, Rep.	2.2436	29
2	Switzerland	3.1924	14	29	Spain	2.9715	18
3	Luxembourg	1.5952	44	30	Malta	3.3308	10
4	Qatar	0.4301	53	31	Cyprus	1.9913	36
5	Iceland	4.4213	2	32	Saudi Arabia	1.5846	45
6	Denmark	3.9482	4	33	Slovenia	3.3988	9
7	United States	5.7490	1	34	Bahrain	1.2660	48
8	Sweden	3.0716	16	35	Bahamas	1.4255	47
9	Australia	3.2530	12	36	Portugal	3.2320	13
10	Ireland	2.9237	19	37	Greece	2.3719	24
11	Singapore	1.6990	41	38	Oman	1.6950	42
12	Netherlands	2.2770	28	39	Estonia	2.0606	31
13	Austria	2.0458	33	40	Czech Republic	2.9956	17
14	Finland	3.9013	5	41	Slovak Republic	1.9867	37
15	Germany	4.1543	3	42	Trinidad & Tobago	0.8689	51
16	Canada	3.1059	15	43	Uruguay	2.3718	25
17	Hong Kong	2.3264	26	44	Lithuania	1.9727	38
18	United Kingdom	2.7565	21	45	Latvia	1.5170	46
19	Belgium	2.5766	22	46	Chile	1.9958	35
20	Kuwait	0.7624	52	47	Poland	2.3067	27
21	United Arab Emirates	0.9038	50	48	Hungary	2.0242	34
22	New Zealand	3.5627	8	49	Panama	1.7983	40
23	France	3.7094	7	50	Croatia	2.4418	23

24	Brunei	2.0590	32	51	Argentina	1.2556	49
25	Japan	3.8495	6	52	Turkey	1.6534	43
26	Israel	2.2127	30	53	Costa Rica	1.8840	39
27	Italy	3.2989	11				

The most noteworthy factor in the countries above the average GHCI value is the amount of GDP in those countries. It should be noted that the fact that the amount of the healthcare expenditures is high in a country does not mean that it has a quality healthcare system. Indeed, the patient satisfaction surveys support this outcome in most of these countries. According to the government policies in these countries, it is a common idea to reduce healthcare expenditures. The countries with high healthcare expenditures (such as Austria, Brunei, Canada, Japan, Netherlands, Sweden, Switzerland, USA, etc.) healthcare systems are needed to be examined. It is inevitable that countries with social and non-social healthcare systems will have an impact on healthcare expenditures.

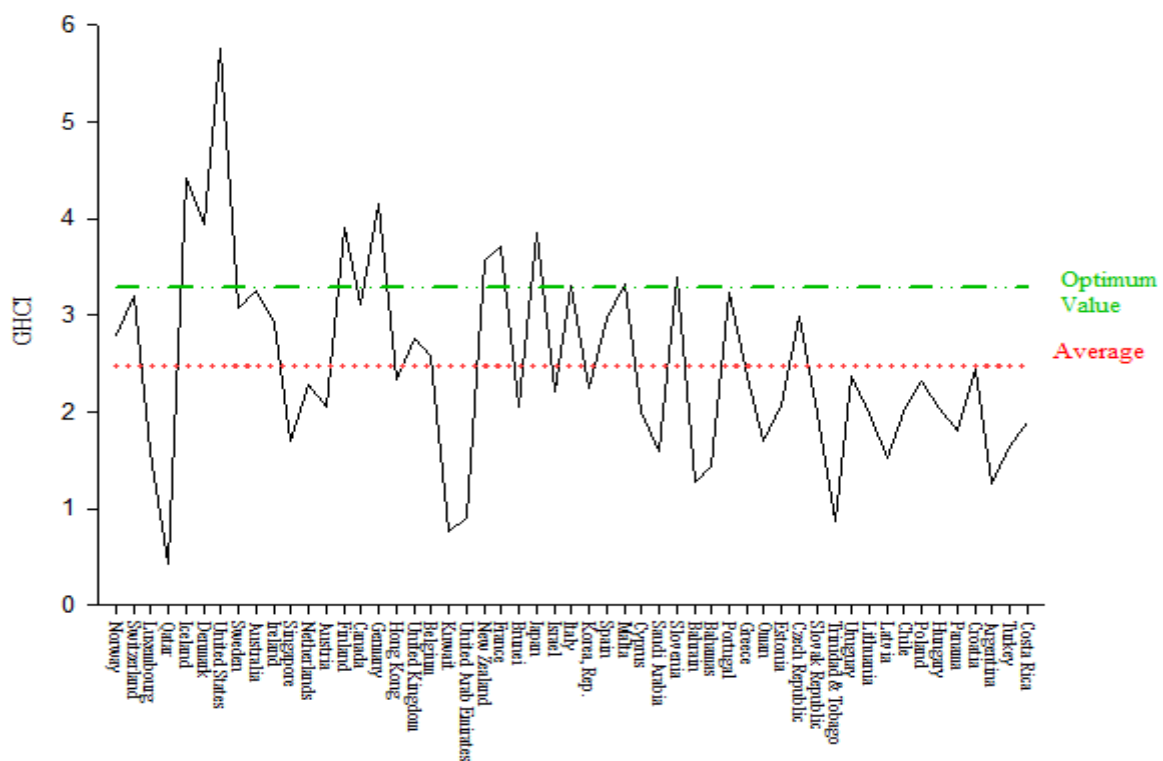


Figure 62:Change of GHCI scores of Countries according to optimum and average values

According to Figure 62, the GHCI score of many countries is below the optimum GHCI value. Only 7 out of 53 countries are above the optimum GHCI value. The GHCI score of 19 countries is above the average GHCI score. Rest of these countries need to improve their GHCI scores immediately.

- **Limitations of this part of the thesis**

This study has also its limitations. For example, the indices such as the number of private and public hospitals of a country were not able to be considered in this study because of lack of information about them. However, our dependent variable as the number of beds or exam rooms instead of the number of hospitals were considered in our optimization models. Another limitation is about the data are relatively short-term. We recommend that may use decision variables to predict long-term global healthcare index five years and beyond. In conclusion, we take a small step to compare several factors that may impact the GHCI. We found that two economic dimensions can be better indicators than HE even though HE is also a good predicting variable for high quality healthcare service. We encourage for further refinement of the GHCI by including healthcare resources (types of hospitals, technicians, technology, etc.) and the components of healthcare (governments as a rule/law maker, pharmaceuticals sector, healthcare insurance companies. etc.) in the index so that it can become a more reliable index. In addition, it may be able to better predict future GHCI.

3.7. Conclusion

A number of methods have been developed to measure quality of healthcare. The aim of this research, which will form the basis of these methods, is to develop optimization models that are provided from the statistical analysis to build GHCI. Factors such as population, average life expectancy, gross domestic product, gross domestic product per capita of the countries, the total number of beds, physicians, and nurses/midwives in the selected countries were considered in this research. The effects of these factors were examined on GHCI and the statistical analysis result of how impressive they were on GHCI was stated. The effect of the factors was considered individually. As a result of the analysis, some factors have a positive effect on the health system while some factors have a negative effect.

The second part that forms the basis of the study is to develop an optimization model in order to use the health economics of the countries more efficiently. In this model, the constraints are derived from the factors that affect the health economics besides healthcare system. Thus, the optimum values of the factors as well as the GHCI data were calculated. Index of healthcare show how good the quality service is in the health field. These indexes determine the ease or difficulty of receiving services of patients from hospitals or other health institutions. Taking these results into consideration, the competitiveness of a country's health system will only be possible if it carries optimum values. It is concluded that countries under these values have low quality of health system or vice versa.

Having a complex structure, healthcare systems are one of the elements that constitute the infrastructures of countries. The health sector is among the largest sectors after the manufacturing sector in the world. Critically, the most important reason for this is the transformation of a health system that is in a social structure into a non-social structure. In countries with economic developments, it is not surprising that developed health systems exist. The fact that people have a high economic advantage in the field of health has opened the way to get a quality service. It is inevitable that there will be large investments economically in order to create quality health service. However, in order to achieve this desired situation, the healthcare economy needs to be managed properly. It is understood that making too much health expenditure (can be regarded as waste) does not guarantee to have a high-quality healthcare system of a country.

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Appendix

A.1. Data of Application of Discreet Event Simulation for Emergency Department



A.1.1. Numerical results of simulation based on 1/24

Table 48: Numerical results of simulation based on 1/24

Rate of Treatment		Counts	Time		Utilization of Healthcare Resources						The Rate of Time		Counts	Rate of Utilization of Healthcare Resource					
MD	AN	PO	WT	LOS	MD ¹	NN	AN ¹	C	ER	TR	WT ¹	LOS ¹	PO ¹	MD ²	NN ¹	C ¹	ER ¹	TR ¹	
95.00%	5.00%	178	91.16	126.87	98.45%	43.76%	43.39%	52.91%	95.84%	39.43%	-174.22%	-67.05%	18.16%	12.73%	11%	11%	26.67%	6.35%	
90.00%	10.00%	186	79.82	111.77	98.45%	44.63%	43.63%	53.99%	95.24%	40.13%	-140.11%	-47.17%	21.68%	12.73%	12%	12%	26.07%	7.05%	
85.00%	15.00%	183	23.71	59.21	89.54%	44.01%	42.63%	52.13%	72.31%	42.64%	28.68%	22.04%	20.40%	3.82%	11%	10%	3.14%	9.56%	
80.00%	20.00%	198	24.01	59.68	89.21%	47.07%	45.85%	55.41%	68.39%	47.18%	27.77%	21.42%	26.43%	3.49%	14%	13%	-0.78%	14.10%	
75.00%	25.00%	171	8.72	46.65	70.23%	41.54%	43.26%	48.04%	40.21%	44.80%	73.77%	38.58%	14.81%	-15.49%	9%	6%	-28.96%	11.72%	
70.00%	30.00%	186	15.73	49.78	74.98%	49.16%	49.44%	52.74%	52.66%	51.26%	52.68%	34.45%	21.68%	-10.74%	17%	11%	-16.51%	18.18%	
65.00%	35.00%	193	10.93	46.28	73.24%	47.65%	48.77%	54.67%	46.29%	50.90%	67.12%	39.06%	24.53%	-12.48%	15%	13%	-22.88%	17.82%	
60.00%	40.00%	186	7.41	42.33	62.59%	48.39%	51.22%	52.63%	36.03%	52.30%	77.71%	44.26%	21.68%	-23.13%	16%	11%	-33.14%	19.22%	
55.00%	45.00%	164	4.36	38.64	46.83%	44.40%	48.60%	45.66%	24.17%	48.70%	86.88%	49.12%	11.18%	-38.89%	12%	4%	-45.00%	15.62%	
50.00%	50.00%	168	4.13	38.34	47.59%	45.45%	50.95%	47.06%	24.55%	50.54%	87.58%	49.52%	13.29%	-38.13%	13%	5%	-44.62%	17.46%	
45.00%	55.00%	172	6.4	40.33	45.79%	47.98%	53.30%	48.48%	23.45%	54.21%	80.75%	46.90%	15.31%	-39.93%	15%	6%	-45.72%	21.13%	
40.00%	60.00%	182	6.55	40.00	42.85%	50.64%	61.59%	51.66%	22.18%	60.29%	80.30%	47.33%	19.96%	-42.87%	18%	10%	-46.99%	27.21%	
35.00%	65.00%	179	7.92	40.11	35.98%	51.89%	65.03%	50.43%	18.18%	61.46%	76.18%	47.19%	18.62%	-49.74%	19%	8%	-50.99%	28.38%	
30.00%	70.00%	189	13.19	45.81	34.43%	53.41%	69.63%	52.84%	17.41%	66.96%	60.32%	39.68%	22.93%	-51.29%	21%	11%	-51.76%	33.88%	
25.00%	75.00%	194	10.49	42.18	30.01%	56.59%	72.65%	55.31%	14.94%	70.07%	68.44%	44.46%	24.91%	-55.71%	24%	13%	-54.23%	36.99%	
20.00%	80.00%	206	22.28	52.37	23.63%	63.82%	85.38%	59.09%	11.96%	81.54%	32.98%	31.04%	29.29%	-62.09%	31%	17%	-57.21%	48.46%	
15.00%	85.00%	193	15.84	45.68	16.55%	59.56%	81.42%	54.46%	8.32%	76.96%	52.35%	39.85%	24.53%	-69.17%	27%	12%	-60.85%	43.88%	
10.00%	90.00%	200	19.08	48.34	10.78%	62.75%	88.28%	56.53%	5.36%	84.11%	42.61%	36.35%	27.17%	-74.94%	30%	14%	-63.81%	51.03%	
5.00%	95.00%	190	19.44	47.01	7.95%	59.06%	82.03%	54.48%	3.95%	76.04%	41.52%	38.10%	23.33%	-77.77%	26%	12%	-65.22%	42.96%	

MD: The rate of patients treated by Medical Doctor,
AN: The rate of patients treated by AN,
WT: The patient's waiting time,
LOS: The patient's length of stay,
MD¹: Utilization rate of Medical Doctors,

PO: The number of patients treated,
NN: Utilization rate of Normal Nurse,
AN¹: Utilization rate of HSN,
C: Utilization rate of Clerks,
ER: Utilization rate of Exam Room,
TR: Utilization rate of Triage Area,
WT¹: The rate of differences of waiting time,

LOS¹: The rate of differences of LOS,
PO¹: Fluctuations rate of the number of patients treated
MD²: The rate of differences of Medical Doctors,
NN¹: The rate of differences of Normal Nurses,
C¹: The rate of differences of Clerks,
ER¹: The utilization rate of differences of Exam room,
TR¹: The utilization rate of differences of Triage Area

A.1.2. Numerical results of simulation based on 7/24

Table 49: Numerical results of simulation based on 7/24

Rate of Treatment		Counts	Time		Utilization of Healthcare Resources						The Rate of Time		Counts	Rate of Utilization of Healthcare Resource					
MD	AN	PO	WT	LOS	MD ¹	NN	AN ¹	C	ER	TR	WT ¹	LOS ¹	PO ¹	MD ²	NN ¹	C ¹	ER ¹	TR ¹	
95.00%	5.00%	1252	140.21	175.58	39.49%	99.03%	43.39%	50.07%	96.98%	35.14%	-212.34%	-97.50%	12.94%	8.65%	7%	7%	22.08%	6.70%	
90.00%	10.00%	1291	69.17	104.57	40.92%	97.40%	43.63%	51.38%	90.08%	37.39%	-54.09%	-17.63%	15.57%	7.02%	8%	8%	15.18%	8.95%	
85.00%	15.00%	1232	19.78	57.97	39.45%	86.73%	42.63%	49.04%	66.10%	37.62%	55.94%	34.79%	11.53%	-3.65%	7%	6%	-8.80%	9.18%	
80.00%	20.00%	1235	18.25	55.26	40.52%	82.39%	45.85%	49.24%	60.96%	39.09%	59.35%	37.84%	11.74%	-7.99%	8%	6%	-13.94%	10.65%	
75.00%	25.00%	1205	11.24	48.42	40.80%	75.33%	43.26%	47.88%	48.71%	41.13%	74.96%	45.53%	9.54%	-15.05%	8%	4%	-26.19%	12.69%	
70.00%	30.00%	1260	13.57	48.88	43.43%	74.45%	49.44%	49.84%	50.05%	44.20%	69.77%	45.02%	13.49%	-15.93%	11%	6%	-24.85%	15.76%	
65.00%	35.00%	1289	10.95	45.58	45.31%	69.63%	48.77%	51.30%	43.98%	46.86%	75.61%	48.73%	15.44%	-20.75%	13%	8%	-30.92%	18.42%	
60.00%	40.00%	1237	6.79	41.95	45.03%	61.07%	51.22%	49.18%	25.01%	48.30%	84.87%	52.81%	11.88%	-29.31%	13%	6%	-49.89%	19.86%	
55.00%	45.00%	1234	7.05	40.88	46.17%	55.72%	48.60%	48.88%	31.92%	49.62%	84.29%	54.02%	11.67%	-34.66%	14%	5%	-42.98%	21.18%	
50.00%	50.00%	1228	6.17	40.24	46.79%	51.35%	50.95%	48.75%	27.90%	52.43%	86.26%	54.74%	11.24%	-39.03%	14%	5%	-47.00%	23.99%	
45.00%	55.00%	1279	7.03	40.64	49.53%	48.39%	53.30%	50.66%	25.84%	56.72%	84.34%	54.29%	14.78%	-41.99%	17%	7%	-49.06%	28.28%	
40.00%	60.00%	1236	5.80	38.63	48.91%	41.46%	61.59%	49.24%	21.80%	57.12%	87.08%	56.55%	11.81%	-48.92%	16%	6%	-53.10%	28.68%	
35.00%	65.00%	1245	6.67	38.95	50.83%	36.60%	65.03%	49.15%	18.93%	60.43%	85.14%	56.19%	12.45%	-53.78%	18%	6%	-55.97%	31.99%	
30.00%	70.00%	1222	7.38	39.01	50.28%	30.42%	69.63%	48.70%	15.32%	60.60%	83.56%	56.12%	10.80%	-59.96%	18%	5%	-59.58%	32.16%	
25.00%	75.00%	1291	13.11	44.26	54.49%	26.97%	71.71%	51.25%	13.80%	68.83%	70.80%	50.21%	15.57%	-63.41%	22%	8%	-61.10%	40.39%	
20.00%	80.00%	1288	12.63	42.76	55.75%	20.99%	74.31%	51.13%	10.58%	70.20%	71.86%	51.90%	15.37%	-69.39%	23%	8%	-64.32%	41.76%	
15.00%	85.00%	1290	12.35	42.18	56.61%	16.87%	77.69%	51.18%	8.42%	72.89%	72.49%	52.55%	15.50%	-73.51%	24%	8%	-66.48%	44.45%	
10.00%	90.00%	1260	12.38	41.13	56.22%	11.36%	77.72%	50.06%	5.68%	72.61%	72.42%	53.73%	13.49%	-79.02%	24%	7%	-69.22%	44.17%	
5.00%	95.00%	1274	14.69	42.76	57.74%	6.87%	80.76%	50.69%	3.42%	75.01%	67.28%	51.90%	14.44%	-83.51%	25%	7%	-71.48%	46.57%	

MD: The rate of patients treated by Medical Doctor,
AN: The rate of patients treated by AN,
WT: The patient's waiting time,
LOS: The patient's length of stay,
MD¹: Utilization rate of Medical Doctors,

PO: The number of patients treated,
NN: Utilization rate of Normal Nurse,
AN¹: Utilization rate of AN,
C: Utilization rate of Clerks,
ER: Utilization rate of Exam Room,
TR: Utilization rate of Triage Area,
WT¹: The rate of differences of waiting time,

LOS¹: The rate of differences of LOS,
PO¹: Fluctuations rate of number of the patients treated
MD²: The rate of differences of Medical Doctors,
NN¹: The rate of differences of Normal Nurses,
C¹: The rate of differences of Clerks,
ER¹: The utilization rate of differences of Exam room,
TR¹: The utilization rate of differences of Triage Area

A.2. The Matrix Table of the Data in the Simulation with the Design of Experiment

Table 50: Data Obtained in Simulated Multi-Level Factorial Design

No	Physicians	Nurses	Clerks	Exam Rooms	Triage Area	WT	PO
1	1.00	1.00	1.00	1.00	1.00	96.00	15.00
2	1.00	1.00	1.00	1.00	2.00	160.00	9.00
3	1.00	1.00	1.00	2.00	1.00	65.45	22.00
4	1.00	1.00	1.00	2.00	2.00	80.00	18.00
5	1.00	1.00	1.00	3.00	1.00	46.45	31.00
6	1.00	1.00	1.00	3.00	2.00	51.43	28.00
7	1.00	1.00	2.00	1.00	1.00	120.00	12.00
8	1.00	1.00	2.00	1.00	2.00	144.00	10.00
9	1.00	1.00	2.00	2.00	1.00	57.60	25.00
10	1.00	1.00	2.00	2.00	2.00	96.00	15.00
11	1.00	1.00	2.00	3.00	1.00	75.79	19.00
12	1.00	1.00	2.00	3.00	2.00	68.57	21.00
13	1.00	2.00	1.00	1.00	1.00	84.71	17.00
14	1.00	2.00	1.00	1.00	2.00	68.57	21.00
15	1.00	2.00	1.00	2.00	1.00	30.00	48.00
16	1.00	2.00	1.00	2.00	2.00	26.67	54.00
17	1.00	2.00	1.00	3.00	1.00	46.45	31.00
18	1.00	2.00	1.00	3.00	2.00	25.71	56.00
19	1.00	2.00	2.00	1.00	1.00	35.12	41.00
20	1.00	2.00	2.00	1.00	2.00	68.57	21.00
21	1.00	2.00	2.00	2.00	1.00	30.64	47.00
22	1.00	2.00	2.00	2.00	2.00	51.43	28.00
23	1.00	2.00	2.00	3.00	1.00	34.29	42.00
24	1.00	2.00	2.00	3.00	2.00	43.64	33.00
25	1.00	3.00	1.00	1.00	1.00	80.00	18.00
26	1.00	3.00	1.00	1.00	2.00	75.79	19.00
27	1.00	3.00	1.00	2.00	1.00	75.79	19.00
28	1.00	3.00	1.00	2.00	2.00	32.00	45.00
29	1.00	3.00	1.00	3.00	1.00	30.00	48.00
30	1.00	3.00	1.00	3.00	2.00	46.45	31.00
31	1.00	3.00	2.00	1.00	1.00	55.38	26.00
32	1.00	3.00	2.00	1.00	2.00	60.00	24.00
33	1.00	3.00	2.00	2.00	1.00	32.00	45.00
34	1.00	3.00	2.00	2.00	2.00	30.00	48.00
35	1.00	3.00	2.00	3.00	1.00	31.30	46.00
36	1.00	3.00	2.00	3.00	2.00	24.41	59.00
37	2.00	1.00	1.00	1.00	1.00	96.00	15.00
38	2.00	1.00	1.00	1.00	2.00	160.00	9.00
39	2.00	1.00	1.00	2.00	1.00	28.80	50.00
40	2.00	1.00	1.00	2.00	2.00	28.80	50.00
41	2.00	1.00	1.00	3.00	1.00	17.14	84.00
42	2.00	1.00	1.00	3.00	2.00	46.45	31.00
43	2.00	1.00	2.00	1.00	1.00	120.00	12.00
44	2.00	1.00	2.00	1.00	2.00	120.00	12.00
45	2.00	1.00	2.00	2.00	1.00	26.67	54.00
46	2.00	1.00	2.00	2.00	2.00	55.38	26.00
47	2.00	1.00	2.00	3.00	1.00	14.12	102.00
48	2.00	1.00	2.00	3.00	2.00	32.73	44.00
49	2.00	2.00	1.00	1.00	1.00	75.79	19.00
50	2.00	2.00	1.00	1.00	2.00	53.33	27.00
51	2.00	2.00	1.00	2.00	1.00	14.26	101.00
52	2.00	2.00	1.00	2.00	2.00	14.69	98.00
53	2.00	2.00	1.00	3.00	1.00	11.61	124.00
54	2.00	2.00	1.00	3.00	2.00	11.61	124.00
55	2.00	2.00	2.00	1.00	1.00	11.43	126.00
56	2.00	2.00	2.00	1.00	2.00	68.57	21.00
57	2.00	2.00	2.00	2.00	1.00	65.45	22.00
58	2.00	2.00	2.00	2.00	2.00	13.21	109.00
59	2.00	2.00	2.00	3.00	1.00	15.16	95.00
60	2.00	2.00	2.00	3.00	2.00	11.08	130.00
61	2.00	3.00	1.00	1.00	1.00	11.25	128.00
62	2.00	3.00	1.00	1.00	2.00	80.00	18.00
63	2.00	3.00	1.00	2.00	1.00	57.60	25.00
64	2.00	3.00	1.00	2.00	2.00	12.10	119.00
65	2.00	3.00	1.00	3.00	1.00	12.20	118.00
66	2.00	3.00	1.00	3.00	2.00	11.16	129.00
67	2.00	3.00	2.00	1.00	1.00	9.93	145.00
68	2.00	3.00	2.00	1.00	2.00	32.73	44.00
69	2.00	3.00	2.00	2.00	1.00	49.66	29.00
70	2.00	3.00	2.00	2.00	2.00	11.80	122.00
71	2.00	3.00	2.00	3.00	1.00	12.31	117.00
72	2.00	3.00	2.00	3.00	2.00	11.90	121.00
73	3.00	1.00	1.00	1.00	1.00	10.59	136.00
74	3.00	1.00	1.00	1.00	2.00	110.77	13.00
75	3.00	1.00	1.00	2.00	1.00	120.00	12.00
76	3.00	1.00	1.00	2.00	2.00	36.92	39.00
77	3.00	1.00	1.00	3.00	1.00	72.00	20.00
78	3.00	1.00	1.00	3.00	2.00	13.33	108.00
79	3.00	1.00	2.00	1.00	1.00	24.83	58.00
80	3.00	1.00	2.00	1.00	2.00	120.00	12.00
81	3.00	1.00	2.00	2.00	1.00	120.00	12.00
82	3.00	1.00	2.00	2.00	2.00	25.26	57.00
83	3.00	1.00	2.00	3.00	1.00	72.00	20.00
84	3.00	1.00	2.00	3.00	2.00	13.98	103.00
85	3.00	2.00	1.00	1.00	1.00	18.95	76.00
86	3.00	2.00	1.00	1.00	2.00	13.09	110.00
87	3.00	2.00	1.00	2.00	1.00	20.00	72.00
88	3.00	2.00	1.00	2.00	2.00	1116	129.00
89	3.00	2.00	1.00	3.00	1.00	9.47	152.00
90	3.00	2.00	1.00	3.00	2.00	13.09	110.00

91	3.00	2.00	2.00	1.00	1.00	20.00	72.00
92	3.00	2.00	2.00	1.00	2.00	11.25	128.00
93	3.00	2.00	2.00	2.00	1.00	10.14	142.00
94	3.00	2.00	2.00	2.00	2.00	13.46	107.00
95	3.00	2.00	2.00	3.00	1.00	13.09	110.00
96	3.00	2.00	2.00	3.00	2.00	11.25	128.00
97	3.00	3.00	1.00	1.00	1.00	10.14	142.00
98	3.00	3.00	1.00	1.00	2.00	12.10	119.00
99	3.00	3.00	1.00	2.00	1.00	12.20	118.00
100	3.00	3.00	1.00	2.00	2.00	9.73	148.00
101	3.00	3.00	1.00	3.00	1.00	9.66	149.00
102	3.00	3.00	1.00	3.00	2.00	12.10	119.00
103	3.00	3.00	2.00	1.00	1.00	12.20	118.00
104	3.00	3.00	2.00	1.00	2.00	10.75	134.00
105	3.00	3.00	2.00	2.00	1.00	10.00	144.00
106	3.00	3.00	2.00	2.00	2.00	11.90	121.00
107	3.00	3.00	2.00	3.00	1.00	12.00	120.00
108	3.00	3.00	2.00	3.00	2.00	10.75	134.00
109	1.00	1.00	1.00	1.00	1.00	96,00	15,00
110	1.00	1.00	1.00	1.00	2.00	137,14	10,50
111	1.00	1.00	1.00	2.00	1.00	57,60	25,00
112	1.00	1.00	1.00	2.00	2.00	75,79	19,00
113	1.00	1.00	1.00	3.00	1.00	47,21	30,50
114	1.00	1.00	1.00	3.00	2.00	51,43	28,00
115	1.00	1.00	2.00	1.00	1.00	87,27	16,50
116	1.00	1.00	2.00	1.00	2.00	125,22	11,50
117	1.00	1.00	2.00	2.00	1.00	60.00	24.00
118	1.00	1.00	2.00	2.00	2.00	90.00	16.00
119	1.00	1.00	2.00	3.00	1.00	57.60	25.00
120	1.00	1.00	2.00	3.00	2.00	54.34	26.50
121	1.00	2.00	1.00	1.00	1.00	70.24	20.50
122	1.00	2.00	1.00	1.00	2.00	60.00	24.00
123	1.00	2.00	1.00	2.00	1.00	31.30	46.00
124	1.00	2.00	1.00	2.00	2.00	30.32	47.50
125	1.00	2.00	1.00	3.00	1.00	30.97	46.50
126	1.00	2.00	1.00	3.00	2.00	25.95	55.50
127	1.00	2.00	2.00	1.00	1.00	40.56	35.50
128	1.00	2.00	2.00	1.00	2.00	72.00	20.00
129	1.00	2.00	2.00	2.00	1.00	30.64	47.00
130	1.00	2.00	2.00	2.00	2.00	36.92	39.00
131	1.00	2.00	2.00	3.00	1.00	30.64	47.00
132	1.00	2.00	2.00	3.00	2.00	27.43	52.50
133	1.00	3.00	1.00	1.00	1.00	60.00	24.00
134	1.00	3.00	1.00	1.00	2.00	56.47	25.50
135	1.00	3.00	1.00	2.00	1.00	56.47	25.50
136	1.00	3.00	1.00	2.00	2.00	31.65	45.50
137	1.00	3.00	1.00	3.00	1.00	31.30	46.00
138	1.00	3.00	1.00	3.00	2.00	34.70	41.50
139	1.00	3.00	2.00	1.00	1.00	46.45	31.00

140	1.00	3.00	2.00	1.00	2.00	60.00	24.00
141	1.00	3.00	2.00	2.00	1.00	36.92	39.00
142	1.00	3.00	2.00	2.00	2.00	39.45	36.50
143	1.00	3.00	2.00	3.00	1.00	26.18	55.00
144	1.00	3.00	2.00	3.00	2.00	25.71	56.00
145	2.00	1.00	1.00	1.00	1.00	82.29	17.50
146	2.00	1.00	1.00	1.00	2.00	110.77	13.00
147	2.00	1.00	1.00	2.00	1.00	27.43	52.50
148	2.00	1.00	1.00	2.00	2.00	27.43	52.50
149	2.00	1.00	1.00	3.00	1.00	16.09	89.50
150	2.00	1.00	1.00	3.00	2.00	33.88	42.50
151	2.00	1.00	2.00	1.00	1.00	90.00	16.00
152	2.00	1.00	2.00	1.00	2.00	102.86	14.00
153	2.00	1.00	2.00	2.00	1.00	25.71	56.00
154	2.00	1.00	2.00	2.00	2.00	41.74	34.50
155	2.00	1.00	2.00	3.00	1.00	14.19	101.50
156	2.00	1.00	2.00	3.00	2.00	21.82	66.00
157	2.00	2.00	1.00	1.00	1.00	65.45	22.00
158	2.00	2.00	1.00	1.00	2.00	51.43	28.00
159	2.00	2.00	1.00	2.00	1.00	17.78	81.00
160	2.00	2.00	1.00	2.00	2.00	14.19	101.50
161	2.00	2.00	1.00	3.00	1.00	11.21	128.50
162	2.00	2.00	1.00	3.00	2.00	11.21	128.50
163	2.00	2.00	2.00	1.00	1.00	11.21	128.50
164	2.00	2.00	2.00	1.00	2.00	60.00	24.00
165	2.00	2.00	2.00	2.00	1.00	66.98	21.50
166	2.00	2.00	2.00	2.00	2.00	13.03	110.50
167	2.00	2.00	2.00	3.00	1.00	14.55	99.00
168	2.00	2.00	2.00	3.00	2.00	11.08	130.00
169	2.00	3.00	1.00	1.00	1.00	11.16	129.00
170	2.00	3.00	1.00	1.00	2.00	45.00	32.00
171	2.00	3.00	1.00	2.00	1.00	44.31	32.50
172	2.00	3.00	1.00	2.00	2.00	12.52	115.00
173	2.00	3.00	1.00	3.00	1.00	12.31	117.00
174	2.00	3.00	1.00	3.00	2.00	10.71	134.50
175	2.00	3.00	2.00	1.00	1.00	10.67	135.00
176	2.00	3.00	2.00	1.00	2.00	41.14	35.00
177	2.00	3.00	2.00	2.00	1.00	54.34	26.50
178	2.00	3.00	2.00	2.00	2.00	12.05	119.50
179	2.00	3.00	2.00	3.00	1.00	12.41	116.00
180	2.00	3.00	2.00	3.00	2.00	11.52	125.00
181	3.00	1.00	1.00	1.00	1.00	10.75	134.00
182	3.00	1.00	1.00	1.00	2.00	73.85	19.50
183	3.00	1.00	1.00	2.00	1.00	99.31	14.50
184	3.00	1.00	1.00	2.00	2.00	35.56	40.50
185	3.00	1.00	1.00	3.00	1.00	37.40	38.50
186	3.00	1.00	1.00	3.00	2.00	13.52	106.50
187	3.00	1.00	2.00	1.00	1.00	25.49	56.50
188	3.00	1.00	2.00	1.00	2.00	70.24	20.50

189	3.00	1.00	2.00	2.00	1.00	102.86	14.00
190	3.00	1.00	2.00	2.00	2.00	24.83	58.00
191	3.00	1.00	2.00	3.00	1.00	60.00	24.00
192	3.00	1.00	2.00	3.00	2.00	13.71	105.00
193	3.00	2.00	1.00	1.00	1.00	21.02	68.50
194	3.00	2.00	1.00	1.00	2.00	13.09	110.00
195	3.00	2.00	1.00	2.00	1.00	16.27	88.50
196	3.00	2.00	1.00	2.00	2.00	10.95	131.50
197	3.00	2.00	1.00	3.00	1.00	10.29	140.00
198	3.00	2.00	1.00	3.00	2.00	13.09	110.00
199	3.00	2.00	2.00	1.00	1.00	16.27	88.50
200	3.00	2.00	2.00	1.00	2.00	10.75	134.00
201	3.00	2.00	2.00	2.00	1.00	10.59	136.00
202	3.00	2.00	2.00	2.00	2.00	13.03	110.50

203	3.00	2.00	2.00	3.00	1.00	13.40	107.50
204	3.00	2.00	2.00	3.00	2.00	10.75	134.00
205	3.00	3.00	1.00	1.00	1.00	10.59	136.00
206	3.00	3.00	1.00	1.00	2.00	12.31	117.00
207	3.00	3.00	1.00	2.00	1.00	12.47	115.50
208	3.00	3.00	1.00	2.00	2.00	10.00	144.00
209	3.00	3.00	1.00	3.00	1.00	10.25	140.50
210	3.00	3.00	1.00	3.00	2.00	12.31	117.00
211	3.00	3.00	2.00	1.00	1.00	12.47	115.50
212	3.00	3.00	2.00	1.00	2.00	10.95	131.50
213	3.00	3.00	2.00	2.00	1.00	9,66	149.00
214	3.00	3.00	2.00	2.00	2.00	12.74	113.00
215	3.00	3.00	2.00	3.00	1.00	12.20	118.00
216	3.00	3.00	2.00	3.00	2.00	10.95	131.50



A.3. Steps of Simulation Systems and Optimization Model with Different Scenarios

Table 51: Steps of Simulation Systems and Optimization Model with Different Conditions

STEP 1: Check-in Process by Clerks						
Scenarios	Treatment Time	Waiting Time	Busy	Idle	Comments	Constraints
1	0	0	*	c_1, c_2	The clerks are idle because there are no patients.	$x_c = 0$
2	t_{c1}	0	c_1	c_2	When a clerk checks in or checks out, the other clerk is idle.	$x_c = 1$
3	t_{c2}	0	c_2	c_1	When a clerk checks in or checks out, the other clerk is idle.	$x_c = 1$
4	(t_{c1}, t_{c2})	$\min \{t_{c1}, t_{c2}\}$	c_1, c_2	*	Both clerks can check in or check out. The patients have to wait.	$x_c = 2$
STEP 2 ₁ : Triage Process						
Scenarios	Treatment Time	Waiting Time	Busy	Idle	Comments	Constraints
1	0	0	*	n_1, n_2, n_3	Nurses are idle for triage	$x_n = 0$ and $x_t = 2$
2	t_{n1}	0	n_1	n_2, n_3	Only one nurse is doing triage. The other nurses are waiting.	$x_n = 1$ and $x_t = 2$
3	t_{n2}	0	n_2	n_1, n_3	Only one nurse is doing triage. The other nurses are waiting.	$x_n = 1$ and $x_t = 2$
4	t_{n3}	0	n_3	n_1, n_2	Only one nurse is doing triage. The other nurses are waiting.	$x_n = 1$ and $x_t = 2$
5	t_{n4}	0	n_1, n_2	n_3	Two nurses are working. A nurse is waiting for triage or treatment.	$x_n = 2$ and $x_t = 2$ and $x_e = 3$
6	t_{n5}	0	n_1, n_3	n_2	Two nurses are working. A nurse is waiting for triage or treatment.	$x_n = 2$ and $x_t = 2$ and $x_e = 3$
7	t_{n6}	0	n_2, n_3	n_1	Two nurses are working. A nurse is waiting for triage or treatment.	$x_n = 2$ and $x_t = 2$ and $x_e = 3$
8	$t_{n1}, t_{n2}, t_{n3}, t_{n4}, t_{n5}, t_{n6}$	$\min \{t_{n1}, t_{n2}, t_{n3}, t_{n4}, t_{n5}, t_{n6}\}$	n_1, n_2, n_3	*	All nurses either treat or triage. The patients have to wait.	$x_n = 3$ and $x_t = 2$ and $x_e = 3$
STEP 2 ₂ : Triage Process in the Triage Area						
Scenarios	Treatment Time	Waiting Time	Busy	Idle	Comments	Constraints
1	0	0	*	t_1, t_2	The triages are idle because there are no patients.	$x_t = 0$
2	t_{n1}, t_{n2}, t_{n3}	0	t_1	t_2	When a triage is busy, the other triage is idle.	$x_t = 1$ and $x_n \leq 2$
3	t_{n1}, t_{n2}, t_{n3}	0	t_2	t_1	When a triage is busy, the other triage is idle.	$x_t = 1$ and $x_n \leq 2$
4	$(t_{n1}, t_{n2}), (t_{n1}, t_{n3}), (t_{n2}, t_{n3})$	$\min \{t_{n1}, t_{n2}, t_{n3}, t_{n4}, t_{n5}, t_{n6}\}$	t_1, t_2	*	Both triage areas are busy. The patients have to wait.	$x_n = 2$ and $x_n = 2$

STEP 3 ₁ : Treatment Process by Physicians						
Scenarios	Treatment Time	Waiting Time	Busy	Idle	Comments	Constraints
2	t_{p1}	0	p_1	p_2, p_3	Only one physician is in the process of treatment. The others are waiting.	$x_p = 0$ and $x_e \leq 3$
3	t_{p2}	0	p_2	p_1, p_3	Only one physician is in the process of treatment. The others are waiting.	$x_p = 1$ and $x_e \leq 3$
4	t_{p3}	0	p_3	p_1, p_2	Only one physician is in the process of treatment. The others are waiting.	$x_p = 1$ and $x_e \leq 3$
5	t_{p4}	0	p_1, p_2	p_3	Two physicians are working. A physician is waiting for treatment.	$x_p = 2$ and $x_e \leq 3$
6	t_{p5}	0	p_1, p_3	p_2	Two physicians are working. A physician is waiting for treatment.	$x_p = 2$ and $x_e \leq 3$
7	t_{p6}	0	p_2, p_3	p_1	Two physicians are working. A physician is waiting for treatment.	$x_p = 2$ and $x_e \leq 3$
8	$t_{p1}, t_{p2}, t_{p3}, t_{p4}, t_{p5}, t_{p6}$	$\min \{t_{p1}, t_{p2}, t_{p3}, t_{p4}, t_{p5}, t_{p6}\}$	p_1, p_2, p_3	*	All Physicians treat the patients. The patients have to wait.	$x_p = 3$ and $x_e = 3$
STEP 3 ₂ : Treatment Process by Nurses						
Scenarios	Treatment Time	Waiting Time	Busy	Idle	Comments	Constraints
1	0	0	*	n_1, n_2, n_3	All Nurses are idle for treatments	$x_n = 2$
2	t_{n1}	0	n_1	n_2, n_3	Only one nurse is doing treatment. The other nurses are waiting.	$x_n = 2$ and $x_e \leq 3$ or $x_t = 2$
3	t_{n2}	0	n_2	n_1, n_3	Only one nurse is doing treatment. The other nurses are waiting.	$x_n = 2$ and $x_e \leq 3$ or $x_t = 2$
4	t_{n3}	0	n_3	n_1, n_2	Only one nurse is doing treatment. The other nurses are waiting.	$x_n = 2$
5	t_{n4}	0	n_1, n_2	n_3	Two nurses are working. A nurse is waiting for triage or treatment.	$x_n = 1$
6	t_{n5}	0	n_1, n_3	n_2	Two nurses are working. A nurse is waiting for triage or treatment.	$x_n = 1$
7	t_{n6}	0	n_2, n_3	n_1	Two nurses are working. A nurse is waiting for triage or treatment.	$x_n = 1$
8	$t_{n1}, t_{n2}, t_{n3}, t_{n4}, t_{n5}, t_{n6}$	$\min \{t_{n1}, t_{n2}, t_{n3}, t_{n4}, t_{n5}, t_{n6}\}$	n_1, n_2, n_3	*	All nurses either treat or triage. The patients have to wait.	$x_n = 0$
STEP 3 ₃ : Treatment Process in the Exam Rooms						
Scenarios	Treatment Time	Waiting Time	Busy	Idle	Comments	Constraints

1	0	0	*	e_1, e_2, e_3	All Exam Rooms are idle for treatment	$x_e = 3$
2	t_{e1}	0	e_1	e_2, e_3	Treatment is done in one exam room only. The others are idle.	$x_e = 2$ and $x_n \leq 2$ or $x_p \leq 2$
3	t_{e2}	0	e_2	e_1, e_3	Treatment is done in one exam room only. The others are idle.	$x_e = 2$ and $x_n \leq 2$ or $x_p \leq 2$
4	t_{e3}	0	e_3	e_1, e_2	Treatment is done in one exam room only. The others are idle.	$x_e = 2$ and $x_n \leq 2$ or $x_p \leq 2$
5	t_{e4}	0	e_1, e_2	e_3	Two exam rooms are used for treatment. An exam room is idle.	$x_e = 1$ and $x_n \leq 1$ or $x_p \leq 1$
6	t_{e5}	0	e_1, e_3	e_2	Two exam rooms are used for treatment. An exam room is idle.	$x_e = 1$ and $x_n \leq 1$ or $x_p \leq 1$
7	t_{e6}	0	e_2, e_3	e_1	Two exam rooms are used for treatment. An exam room is idle.	$x_e = 1$ and $x_n \leq 1$ or $x_p \leq 1$
8	$t_{e1}, t_{e2}, t_{e3}, t_{e4}, t_{e5}, t_{e6}$	$\min\{t_{e1}, t_{e2}, t_{e3}, t_{e4}, t_{e5}, t_{e6}\}$	e_1, e_2, e_3	*	All nurses either treat or triage. The patients have to wait.	$x_e = 0$ and $x_n \leq 3$ or $x_p \leq 3$
STEP 1: Check-out Process by Clerks						
Scenarios	Treatment Time	Waiting Time	Busy	Idle	Comments	Constraints
1	0	0	*	c_1, c_2	The clerks are idle because there are no patients.	$x_c = 2$
2	t_{c1}	0	c_1	c_2	When a clerk checks in or checks out, the other clerk is idle.	$x_c = 1$
3	t_{c2}	0	c_2	c_1	When a clerk checks in or checks out, the other clerk is idle.	$x_c = 1$
4	(t_{c1}, t_{c2})	$\min\{t_{c1}, t_{c2}\}$	c_1, c_2	*	Both clerks can check in or check out. The patients have to wait.	$x_c = 0$

A.5. The values of Factors of GHCI

Table 52: The values of Factors of GHCI

No	Country	Population	National Income Per Capita	Gross Domestic Product (Million \$)	Life Expectancy	Number of Beds	Number of Physicians	Number of Nurses and Midwives	Healthcare Expenditures (% of GDP)
1	Norway	5305383	\$ 82,330	\$ 370,557	82.02	3.3000	4.4200	17.4101	9.7197
2	Switzerland	8476005	\$ 81,240	\$ 659,827	83.49	5.0000	4.1100	17.8100	11.6593
3	Luxembourg	583455	\$ 76,660	\$ 59,948	82.26	5.4006	2.8606	12.3300	6.9377
4	Qatar	2639211	\$ 75,660	\$ 152,469	78.62	1.2000	1.9601	5.7002	2.1873
5	Iceland	335025	\$ 56,990	\$ 20,047	83.06	3.1998	3.6505	16.3510	8.8592
6	Denmark	5733551	\$ 56,730	\$ 306,143	80.70	3.4999	3.6480	16.8100	10.8051
7	United States	324459463	\$ 56,180	\$ 18,569,100	79.50	2.9000	2.5540	9.8840	17.1408
8	Sweden	9910701	\$ 54,630	\$ 511,000	82.68	2.7000	4.1070	11.8920	11.9297
9	Australia	24450561	\$ 54,420	\$ 1,204,616	82.91	3.9000	3.3740	12.3340	9.4223
10	Ireland	4761657	\$ 52,560	\$ 294,054	81.43	2.9000	2.7799	12.4001	7.7833
11	Singapore	5708844	\$ 51,880	\$ 296,966	83.61	2.0001	1.9130	5.6460	4.9228
12	Netherlands	17035938	\$ 46,310	\$ 770,845	82.00	4.7000	3.3130	8.5170	10.8973
13	Austria	8735453	\$ 45,230	\$ 386,428	81.97	7.5999	5.0600	8.1920	11.2055
14	Finland	5523231	\$ 44,730	\$ 236,785	81.39	5.5000	3.0010	14.5131	9.6801
15	Canada	36624199	\$ 43,660	\$ 1,529,760	82.56	2.7000	2.4700	9.5010	10.4496
16	Germany	82114224	\$ 43,660	\$ 3,466,757	81.45	8.2000	4.0390	13.4800	11.2970
17	Hong Kong	7364883	\$ 43,240	\$ 320,912	84.46	5.3076	1.3201	7.1129	5.7000
18	United Kingdom	66181585	\$ 42,390	\$ 2,618,886	81.17	2.9000	2.8100	8.4360	9.1155
19	Belgium	11429336	\$ 41,860	\$ 466,366	81.35	6.5300	2.9700	10.0780	10.5947
20	Kuwait	4136528	\$ 41,680	\$ 114,041	74.77	2.1999	1.9499	4.7291	3.0428

21	UAE	9400145	\$ 40,480	\$ 348,743	77.46	1.1000	1.5600	3.0610	3.6439
22	New Zealand	4705818	\$ 39,070	\$ 185,017	82.36	2.2999	2.8501	10.7199	11.0298
23	France	64979548	\$ 38,950	\$ 2,465,454	82.74	6.4000	3.1870	10.6100	11.5395
24	Brunei	428697	\$ 38,520	\$ 11,400	79.42	2.7992	1.4696	8.1946	26.4912
25	Japan	127484450	\$ 38,000	\$ 4,939,384	84.00	13.7000	2.2970	10.7970	10.2287
26	Israel	8321570	\$ 36,190	\$ 318,744	82.93	3.3700	3.6200	5.2640	7.8085
27	Italy	59359900	\$ 31,590	\$ 1,849,970	83.69	3.4000	3.9500	6.4750	9.2479
28	Korea, Rep.	50982212	\$ 27,600	\$ 1,411,246	82.63	10.3000	2.1850	5.6700	7.3731
29	Spain	46354321	\$ 27,520	\$ 1,232,088	83.13	3.1000	3.8200	5.3580	9.0299
30	Malta	430835	\$ 24,140	\$ 10,949	81.07	4.8000	3.7509	8.6669	9.7543
31	Cyprus	1179551	\$ 23,680	\$ 19,802	80.67	3.4996	2.5001	3.9083	7.3679
32	Saudi Arabia	32938213	\$ 21,750	\$ 646,438	74.72	2.1000	2.5700	5.2070	4.6841
33	Slovenia	2079976	\$ 21,660	\$ 43,991	80.92	4.6001	2.6231	8.6112	9.2337
34	Bahrain	1492584	\$ 21,480	\$ 31,859	76.99	2.0997	0.9400	2.4448	4.9813
35	Bahamas	395361	\$ 21,020	\$ 9,047	75.88	2.9011	2.7165	3.9888	7.7374
36	Portugal	10329506	\$ 19,850	\$ 204,565	81.64	3.4000	4.2600	6.3770	9.5011
37	Greece	11159773	\$ 18,960	\$ 194,559	81.47	4.8000	6.2600	3.4400	8.0844
38	Oman	4636262	\$ 18,080	\$ 66,293	77.40	1.7001	1.9699	3.3449	3.5539
39	Estonia	1309632	\$ 17,750	\$ 23,137	77.24	5.3000	3.3200	5.9711	6.3794
40	Czech Republic	10618303	\$ 17,570	\$ 192,925	79.06	6.8000	3.6771	8.3260	7.4112
41	Slovak Republic	5447662	\$ 16,810	\$ 89,552	76.65	6.0000	3.3870	6.0780	8.0545
42	Trinidad/Tobago	1369125	\$ 15,680	\$ 20,989	70.72	2.7003	1.1752	3.5621	5.9317
43	Uruguay	3456750	\$ 15,230	\$ 52,420	77.66	2.9999	3.7359	5.5480	8.5807
44	Lithuania	2890297	\$ 14,770	\$ 42,739	73.73	7.0000	4.3300	7.9511	6.5514
45	Latvia	1949670	\$ 14,630	\$ 27,677	74.52	5.9000	3.2200	5.0321	5.8821
46	Chile	18054726	\$ 13,530	\$ 247,028	82.52	2.1000	1.0300	0.1450	7.7858
47	Poland	38170712	\$ 12,680	\$ 469,509	77.94	6.5000	2.2270	5.7300	6.3503

48	Hungary	9721559	\$ 12,570	\$ 124,343	75.55	7.2000	3.3200	6.5680	7.4005
49	Panama	4098587	\$ 12,140	\$ 55,188	78.10	2.2000	1.5940	2.3301	8.0253
50	Croatia	4189353	\$ 12,110	\$ 50,425	77.85	5.9799	3.0210	6.1410	7.8037
51	Argentina	44271041	\$ 11,960	\$ 545,866	76.82	4.7000	3.7620	0.4820	4.7860
52	Turkey	80745020	\$ 11,180	\$ 857,749	76.06	2.5000	1.7500	2.5190	5.4150
53	Costa Rica	4905769	\$ 10,840	\$ 57,436	79.99	1.2000	1.1501	0.7960	9.3130

Resume

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PERSONAL INFORMATION

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EDUCATION

- RA -Mechanical Engineering, Bayburt University, Bayburt, Turkey, (2015- to present)
- Ph.D. Student, Industrial Engineering, Marmara University, Istanbul, Turkey, (2013-Present)
- Ph.D. Research, Industrial Systems Engineering and Product Design, Ghent University, Ghent, Belgium, (2015-2016)
- Ph.D. Research, Industrial Engineering, Clemson University, Clemson, SC, USA, (2013-2015)
- MS., Healthcare Systems Engineering/ISE, Lehigh University, Bethlehem, USA, 2013
- BS, (with Honors), Industrial Engineering, Selcuk University, Konya, Turkey, 2009
- BS, (with Honors), Industrial Engineering, Eastern Mediterranean University, North Cyprus, 2006

INTERNS & INDUSTRY EXPERIENCES & SKILLS & SCHOLARSHIPS

- September 2004-June 2006: Department of Industrial Engineering, Eastern Mediterranean University, Famagusta, North Cyprus, Full Scholarship (Tuition, Fees, Housing).
- July 2007-August 2007: Internship in Ford Motor Company, Quality Control & Human Resources, Eskisehir, TURKEY.
- July 2008-August 2008: Internship in GAP (Guneydogu Textile), Production Planning, Malatya, TURKEY.
- June 2012-September 2012: Internship in Lehigh Valley Hospital, Optimization and Simulation, Bethlehem, PA, USA
- June 2012-December 2012: Capstone Project I, using computer simulation modeling and optimization to reduce waiting time and increase capacity in Cancer Center at Lehigh Valley Hospital. Lehigh Valley, Bethlehem, PA, USA (Fund: \$7,200)
- September 2012-January 2013: Capstone Project II, having 80% of patients enter and exit the urgent care center in 1 hour at St. Luke's Hospital, Bethlehem, PA, USA (Fund: \$-)
- September 2012-December 2013: Project Coordinator and Consultant, Clinic throughout optimization with physician residency program Hospital, Bethlehem, PA, USA (Fund: \$-)
- September 2012- December 2013: Project Coordinator and Consultant, Data mining for indicators of likelihood of re-hospitalization with St. Luke's Hospital, Bethlehem, PA, USA.
- March 2013-July 2013: Simulation Specialist, to determine the feasibility of using simulation modeling of healthcare provider practice to quantify the incremental burden of REMS requirements, Washington, DC (Funds: \$10,500).
- January 2010-June 2016: Scholarship from Ministry of National Education of Turkey to pursue MSc and Ph. D. degrees in USA. Award covers tuition, salary, and health insurance.
- May 2014: Six Sigma Green Belt, The center of Excellence in Quality, Clemson University
- June 2018-June 2019: Marmara University Scientific Research Fund, The Project no: FEN-C-DRP-

110618-0344. (Funds: 22.900,00 ₺).

- Software: AMPL, Arena, Flexsim Simulation, Latex, Lindo/Lingo, Minitab, Mathematica, Maple, Numbers, Pascal, R, SAS, and Sigma Plot.

RESEARCH INTERESTS

- Optimization (Stochastic, Nonlinear Programming, Heuristic Modelling),
- Statistics (Design of Experiments-Quality Characteristics),
- Simulation (Discrete and Continuous Event Simulation in Healthcare Area),
- Healthcare Management, Quality in Healthcare (Quality Tools, MCDM, Lean Hospitals, Six Sigma)

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