UNIVERSIDADE FEDERAL DE MINAS GERAIS

PROGRAMA DE PÓS-GRADUAÇÃO EM

ENGENHARIA MECÂNICA

DESIGNING AND BUILDING AN INTERACTIVE SIMULATION-BASED DECISION SUPPORT SYSTEM IN HEALTHCARE INDUSTRY

MILAD YOUSEFI

Belo Horizonte, 7 de Abril de 2017

Milad Yousefi

DESIGNING AND BUILDING AN INTERACTIVE SIMULATION-BASED DECISION SUPPORT SYSTEM IN HEALTHCARE INDUSTRY

This work is presented to the Program of Graduate Studies in Mechanical Engineering of Federal University of Minas Gerais for obtaining a PhD degree in Mechanical Engineering.

Concentration Area: Operational research

Supervisor: Ricardo Poley Martins Ferreira

Federal University of Minas Gerais – UFMG

Belo Horizonte

Engineering School of UFMG

2017

UNIVERSIDADE FEDERAL DE MINAS GERAIS
PROGRAMA DE PÓS-GRADUAÇÃO EM ENGENHARIA MECÂNICA
Av. Antônio Carlos, 6627 - Campus Universitário
31270-901 – Belo Horizonte – MG
Tel.:+55 31 3409.5145
E-mail: cpgmec@demec.ufmg.br

"DESIGNING AND BUILDING AN INTERACTIVE SIMULATION-BASED DECISION SUPPORT SYSTEM IN HEALTHCARE INDUSTRY"

MILAD YOUSEFI

Tese submetida à Banca Examinadora designada pelo Colegiado do Programa de Pós-Graduação em Engenharia Mecânica da Universidade Federal de Minas Gerais, como parte dos requisitos necessários à obtenção do título de **"Doutor em Engenharia Mecânica"**, na área de concentração de **"Projeto Mecânico".**

Tese aprovada no dia 07 de abril de 2017.

Por:

Prof. Ricardo Poley Martins Ferreira
Orientador - Departamento de Engenharia Mecânica/UFMG

Prof. Denilson Laudares Rodrigues
Pontifícia Universidade Católica de Minas Gerais

Prof. Henrique Pacca Loureiro Luna
Universidade Federal de Alagoas

Prof. Henrique Oswaldo da Gama Torres
Departamento de Clínica Médica/UFMG

Prof. Ricardo Luiz Utsch de Freitas Pinto
Departamento de Engenharia Mecânica/UFMG

Prof. Eduardo Bauzer Medeiros
Departamento de Engenharia Mecânica/UFMG

Federal University of Minas Gerais

Program of Graduation in Mechanical Engineering

Av. Antônio Carlos, 6627 - Pampulha - 31.270-901 - Belo Horizonte – MG.
Tel.: +55 31 3499-5145 - Fax. +55 31 3443-3783
www.demec.ufmg.br - Email: cpgmec@demec.ufmg.br

DESIGNING AND BUILDING AN INTERACTIVE SIMULATION-BASED DECISION SUPPORT SYSTEM IN HEALTHCARE INDUSTRY

MILAD YOUSEFI

The dissertation is defended on April 7, 2017. The examiner bank selected by the board of Program of Graduation in Mechanical Engineering of Federal University of Minas Gerais (UFMG) for this qualification exam which is for defending the thesis given for obtaining a PhD degree in the area of operational research includes:

Prof. Ricardo Poley Martins Ferreira
Supervisor- Doctor, Department of Mechanical Engineering, UFMG

Prof. Denilson Laudares Rodrigues
Examiner- Doctor, Pontifícia Universidade Católica de Minas Gerais

Prof. Henrique Pacca Loureiro Luna
Examiner – Doctor, Universidade Federal de Alagoas

Prof. Henrique Oswaldo da Gama Torres
Examiner – Doctor, Departamento de Clínica Médica, UFMG

Prof. Ricardo Luiz Utsch de Freitas Pinto
Examiner - Doctor, Department of Mechanical Engineering, UFMG

Prof. Eduardo Bauzer Medeiros
Examiner – Doctor, Department of Mechanical Engineering, UFMG

Belo Horizonte, April 7, 2017

*"Os livros não mudam o mundo,
quem muda o mundo são as pessoas.
Os livros só mudam as pessoas."*

Mário Quintana

To my beloved parents, Khadijeh and Majid.

To my siblings Mohsen, Mehri, Mojtaba and Moslem.

Acknowledgment

This project would not have been possible without the support of many people. I would like to express my sincere thanks to my supervisor Prof. Dr. Ricardo Poley Martins Ferreira for his support during this research. Thanks to the Universidade Federal de Minas Gerais for providing me with the financial means to complete this project.

I am indebted to all those who supported me in first months of my stay in Brazil. My deep appreciation for Breno Fonseca and Paul Silva and their families.

I would like to thank Nathalia Paiva Costa and her lovely family for their hospitality, support, care and love.

My special thanks go to my brother, Dr. Moslem Yousefi, for his invaluable support during the course of this study. I would not have been able to carry out this research if it was not his support and love.

I would also like to thank my parents for their patience and love throughout all these years. My thanks also go to my sister Mehri and my brothers Mohsen and Mojtaba who have been always of great help and encouragement to me.

I am very grateful to Dr. Lucas Coimbra, Coordinator of the Risoleta Tolentino Neves Hospital Emergency Department for assistance with the simulation design and data collection, and Dr. Henrique Torres, General Manager of the Hospital for giving me the opportunity of doing my project in HRTN.

And finally, last but by no means least, thanks to my friends, Syed Babar Jamal, Giancarlo Drumond, Sara Joy Carminati, Sorour, Mahrouz, Masoud, and Reza who endured this long process with me, always offering support and love.

Abstract

Long length of stay and overcrowding in emergency departments (EDs) are two common problems in the healthcare industry. To decrease the average length of stay (ALOS) and tackle overcrowding, numerous resources, including the number of doctors, nurses and receptionists need to be adjusted, while a number of constraints are to be considered at the same time. In the first part of this thesis, a novel group decision making approach is implemented and each staff agent took part in the process of allocating resources based on their observation in their respective sections, which gave the system the advantage of utilizing all the available human resources during the workday by being allocated to a different section. In this simulation, unlike previous studies, all staff agents took part in the decision-making process to re-allocate the resources in the emergency department. The simulation modeled the behavior of patients, receptionists, triage nurses, emergency room nurses and doctors. Patients were able to decide whether to stay in the system or leave the department at any stage of treatment. In order to evaluate the performance of this approach, 6 different scenarios were introduced. In each scenario, various key performance indicators were investigated before and after applying the group decision-making. The outputs of each simulation were number of deaths, number of patients who leave the emergency department without being attended, length of stay, waiting time and total number of discharged patients from the emergency department. Applying the self-organizing approach in the simulation showed an average of 12.7 and 14.4% decrease in total waiting time and number of patients who left without being seen, respectively. The results showed an average increase of 11.5% in total number of discharged patients from emergency department.

The second part of the study, we implemented an efficient method based on agent-based simulation, machine learning and evolutionary algorithms (EAs) to determine near optimum resource allocation in an emergency department in Hospital Risoleta Tolentino Neves (HRTN), a teaching hospital in the capital of Minas Gerais state of Brazil, Belo Horizonte. The proposed decision support system (DSS) can effectively explore the entire domain of all 19 variables and identify an improved resource allocation. A model of the system needs to be run several thousand times through the algorithms evolution process to evaluate each solution, hence the process is computationally expensive. To overcome this drawback, a robust metamodel is initially constructed based on an agent-based system simulation. The simulation exhibits ED performance with various resource allocations and trains the metamodel. The metamodel is created with an ensemble of the adaptive neuro-fuzzy inference system (ANFIS), feedforward neural network (FFNN) and recurrent neural network (RNN) using the adaptive boosting (AdaBoost) ensemble algorithm. The proposed simulation-based optimization approach is tested in a public ED, and it is shown to decrease the ALOS in this ED case study by 14%. Additionally, the proposed metamodel shows a 26.6% improvement compared to the average results of ANFIS, FFNN and RNN in terms of mean absolute percentage error (MAPE).

Keywords: Simulation-based optimization, Decision support system, Metamodeling, Healthcare Industry, Patient flow, Evolutionary Algorithms

Resumo

O Longo período de permanência e superlotação em departamentos de emergência, são dois problemas comuns no setor de saúde. Para diminuir o tempo médio de permanência e combater a superlotação, é necessário ajustar inúmeros recursos, incluindo o número de médicos, enfermeiros e recepcionistas, ao mesmo tempo que devem ser consideradas várias restrições. Na primeira parte desta tese, foi implementada uma nova abordagem de tomada de decisão de grupo. Cada agente de pessoal participou do processo de alocação de recursos com base em sua observação em suas respectivas seções, o que deu ao sistema a vantagem de utilizar todos os recursos humanos disponíveis durante a jornada de trabalho, sendo alocada para uma seção diferente. Nesta simulação, ao contrário dos estudos anteriores, todos os agentes do pessoal participaram do processo de tomada de decisão para re-alocar os recursos no departamento de emergência. A simulação modelou o comportamento de pacientes, recepcionistas, enfermeiros de triagem, enfermeiros de emergência e médicos. Os pacientes foram capazes de decidir se deveriam permanecer no sistema ou deixar o departamento em qualquer fase do tratamento. Para avaliar o desempenho desta abordagem, foram introduzidos 6 cenários diferentes. Em cada cenário, vários indicadores-chave de desempenho foram investigados antes e depois de aplicar a tomada de decisão do grupo. As saídas de cada simulação foram número de mortes, número de pacientes que deixaram o serviço de emergência sem serem atendidos, tempo de permanência, tempo de espera e número total de pacientes descarregados do departamento de emergência. A aplicação da abordagem auto-organizada na simulação mostrou uma média de 12,7 e 14,4% de redução no tempo total de espera e número de pacientes que deixaram sem ser vistos, respectivamente. Os resultados mostraram um aumento médio de 11,5% no número total de pacientes descarregados do serviço de emergência.

A segunda parte do estudo, implementou um método eficiente baseado em simulação por agentes e algoritmos evolutivos para determinar a alocação de recursos quase que ideal em um departamento de emergência no Hospital Risoleta Tolentino Neves (HRTN), um hospital de ensino na capital do estado de Minas Gerais, Belo Horizonte. O sistema de apoio à decisão proposto, pode efetivamente explorar todo o domínio de todas as 19 variáveis e identificar uma melhor alocação de recursos. Um modelo do sistema precisa ser executado milhares de vezes através do processo de evolução dos algoritmos para avaliar cada solução, portanto, o processo é computacionalmente caro. Para superar esta desvantagem, um metamodelo robusto é construído inicialmente baseado em uma simulação de sistema baseada em agentes. A simulação exibe o desempenho do departamento de emergência com várias alocações de recursos e treina o metamodelo. O metamodelo é criado com um conjunto do sistema de “adaptive neuro-fuzzy inference system” (ANFIS), “feedforward neural network” (FFNN) e “recurrent neural network” (RNN) usando o algoritmo de ajuste de “adaptive boosting” (Adaboost). A abordagem proposta de otimização baseada em simulação é testada em um departamento de emergência público, e é mostrado para diminuir o tempo médio de permanência neste estudo de caso de departamento de emergência em 14%. Adicionalmente, o metamodelo proposto apresenta melhora de 26,6% em relação aos resultados médios de ANFIS, FFNN e RNN em termos de erro médio absoluto de porcentagem (MAPE).

Palavras-chave: Otimização baseada em simulação, Sistema de apoio à decisão, Metamodelagem, Indústria de saúde, Fluxo de pacientes, Algoritmos evolutivos

Nomenclature

ABMS	Agent-based modelling and simulation
ABM	Agent-based model
ABS	Agent-based system
APACHE II	Acute Physiology and Chronic Health Evaluation II
ALOS	Average length of stay
ANN	Artificial neural network
CA	Cellular Automata
EA	Evolutionary algorithm
DSS	Decision support system
DES	Discrete-event simulation
ED	Emergency department
ESI	Emergency Services Interface
ERMIS	Emergency room management information system
LOS	Length of stay
MAS	Multi-agent system
GA	Genetic algorithm
MICA	Modified imperialist competitive algorithm
ICA	Imperialist competitive algorithm
ICU	Intensive Care Unit
PSO	Particle swarm optimization
KPI	Key performance indicator
LWBS	Leave without being seen

Table of Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1. Introduction

Decision making is defined as a logical process of selecting a choice among available alternatives. A decision maker needs to study and consider positive and negative aspects of each option to make a good decision. Moreover, a good decision making needs to forecast the outcome of each option. Small decisions might be taken in few seconds or minutes but when a decision can influence the performance of a complex system with large number of decision variables, making the right decision may not be an easy task. More information about the system makes the decision makers to take better decisions with less risk of failure. Decision support systems (DSSs) are interactive computer based tools that help decision makers providing information about their problems. A DSS uses different sources including documents, data, communication technologies, knowledge to increase the ability of the decision makers.

Emergency departments (EDs) in 50% of the cases are the main entrance of hospitals that receive patients with different illnesses or injuries. In general, an ED consists of an admission section, triage room, laboratory, X-ray section and different treatment sectors such as orthopedic, pediatric, suture section etc. As it can be seen in a schematic ED in Figure 1-1, patients arrive to the ED by walk, with an ambulance or in police custody after being admitted in admission section, patients go to triage room to be classified based on their acuity. In triage room a triage nurse indicates the patients to the related section. Those who needs further examinations go to laboratory and X-ray then patients will be discharged from ED or they go to the observation room to complete their treatments.

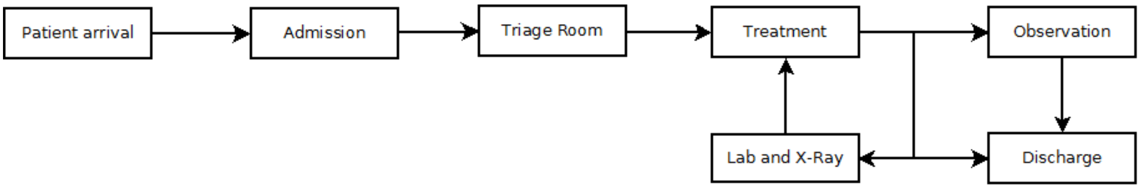

Figure 1-1. A simplified flow of patients at the emergency department in different sections.

Various types of the DSS including status inquiry systems, data analysis systems, information analysis systems, accounting systems and model based systems are used in manufacturing as well as service industries to make decisions. The latest one acts as the stimulation models or the optimization models which can be applied in resource planning, scheduling and etc. As it can be seen in Figure 1-2 a typical DSS has three main components, the user interface, database and the model.

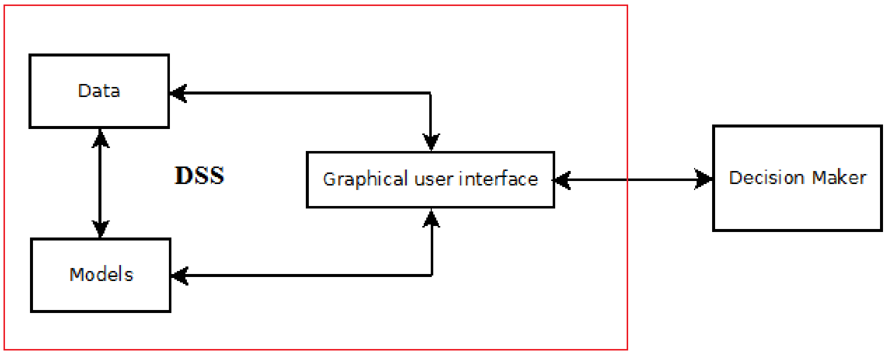

Figure 1-2. Three main components of a decision support system.

Agent-based modelling (ABM) is a relatively new concept that has been used in vast variety of simulation applications including social sciences, economics, management, biology and engineering. Agent-based modelling and simulation (ABMS) consists of group of agents that are able to interact with each other and learn in the process of the simulation. They are also capable to make decisions and participate in the self-organizing (Macal & North, 2010). These agents' abilities make ABMS a popular tool to simulate a range of complex systems from modeling an ancient civilization to market planning for a new product in a manufacturing system (Kohler, Gumerman & Reynolds, 2005). Study the relevant literature of ABMS shows that they are also able to model the dynamic systems and behavior of humans or animals and their interactions (Bonabeau, 2002).

1.2. Problem statement

Making almost any decision in complex systems is a difficult task and it can be more complex when high budgets are involved. The complexity and interdisciplinarity of healthcare industry problems make this industry one of the attention centers of computer-based simulation studies to provide a proper tool for interaction between decision makers and experts.

Healthcare industry is a semi-autonomous unit that operates 24 hours a day, seven days a week, including holidays. Therefore, interrupting their system in order to evaluate their performance and efficiency is almost impossible. Healthcare industry, like most of service industries deals with humans and their interactions. Having human behavior can be considered as one of the most important differences between manufacturing industry and service industry. The nature of human behavior makes any system complex to be simulated. More importantly, healthcare industry in general and particularly emergency departments (EDs) deal with human health. Therefore, an error in ED procedures may lead to disability or death. In general, public hospitals operate under several constraints such as: budget, expert staff, tools etc. In some cases, these constraints are incompatible with each other. Patients arrive to EDs with different health issues and with different levels of acuity and EDs must provide the best service and treatment to all of them. In any stage of treatment, patients can decide to leave the ED based on their experiences or their observations and later they might come back eventually with more problems. Patients with different levels of acuity and different background might have different reactions to waiting time in an ED.

EDs are one of the most overcrowded units in healthcare industry and it has been more than 2 decades that this problem considered as a worldwide problem. This problem can be found from United States to United Kingdom and China. Still there is no available comprehensive tool for analyzing EDs overcrowding and as a result, majority of patients in public health system are suffering from long length of stay (LOS) while hospital managers are struggling with shortage in budget and resources in EDs.

1.3. Objectives of the study

As mentioned in the problem statement section, the systems which are involved with human interactions are more complex to be simulated. In most studies, the differences between manufacturing and service industry are neglected in developing DSS. Therefore, this study tries to propose a DSS with considering human effects in the healthcare industry as one of the most complex examples of service industry. The main objectives of this study can be listed as bellow:

1. To develop a framework for modeling the patient flow and agent based simulation (ABS) in healthcare industry.

2. To propose and develop a novel integrated DSS.
3. To implement a simulation-based decision support tool in a real world based case study.
4. To find the near optimum resource planning in a real world based case study.

1.4. Importance of the study

Although applications of ABS in healthcare industry are becoming a trend and enormous number of papers can be found in the literature, most of these studies have been done in developed countries and to the best of our knowledge these studies have been so limited in Brazil. Healthcare industry is a high cost industry therefore, the ongoing economic crisis in the country leads the health sectors in a critical situation. In some recent cases, the crisis makes some EDs to close some of their sections to be able to continue their routine. A proper resource planning using DSS and artificial intelligence can reduce the risk of inappropriate resource planning.

1.5. Thesis structure

The thesis is structured as follows: Chapter 2 presents a literature review on applications of ABS in different fields of study and its application in EDs. Chapter 3 gives a short description of used research methodologies in this research including ABS, Genetic Algorithms (GAs), Imperialist Competitive Algorithm (ICA), Cellular Automata (CA) and the proposed metamodel approach. Chapter 4 presents the results of the study as well as its contributions. This chapter includes the results from the general ED example extracted from literature and the results from the real case study from an ED in Hospital Risoleta Tolentino Neves (HRTN) located in Belo Horizonte, the capital of Brazilian state of Minas Gerais. Finally, Chapter 5 represents the conclusions and future studies. A summary of published papers based on this research can be found in the Appendix section.

Chapter 2

Literature Review

2.1. Introduction

In this chapter, in order to better understanding of the problem, a comprehensive literature review is conducted on relevant subjects including agent based simulation and its applications in healthcare industry, optimization approaches with focus on EDs and metamodeling approaches. To conduct this literature review, various resources were studied through Universidade Federal de Minas Gerais (UFMG) library data base. Due to fast changes in this field of study, the research from more than 20 years ago were not included, except to explain basic concepts.

2.2. Agent based simulation

Agent-based models (ABMs) are systems consist of a set of agents. Each of these elements have their own characteristics and attributes and they can interact with each other based on a set of rules and a given environment. Since these systems contain a set of agents these systems are also called multi-agent systems (MASs) and agent-based-simulation (ABS) in the literature. Applications of ABS including but not limited to social sciences and economics. All these systems have one factor in common that is the structure of them. All these systems can be designed through a network of elements (agents) (Billari, 2006; Conte, Hegselmann, & Terna, 1997). MASs are able to model systems and their features to forecast their behaviors when they face different conditions. These systems are capable to experiment different potential substitute decisions. Changing in settings of ABSs makes them to make different decisions have different reactions to the same condition and they are learning systems (Axelrod, 1997).

The elements of ABSs (agents) are monitoring their environment as well as other agents in the system. The monitoring process is continuous therefore; agents are able to react to changes in their environment quickly. In general, when a problem is highly dynamic, this ability of ABS makes them able to have higher degree of reactiveness and that helps them to find proper solutions easier. The other types of studies that can benefit the advantages of ABS are optimization problems. Because optimization approaches generally are computationally expensive. The number of parameters and decision variables of problems will make them even more complex and more time consuming.

Characteristics of ABS make them able to be implemented in different fields of study such as facility location, logistics, supply chain planning, scheduling and transportation as a heuristic approach. All these problems have distributed, heterogeneous and complicated domains. Different literature review studies have shown the applications of ABS in different fields of study.

Shen et al., (2006) provide a literature review on applications of ABS in manufacturing process planning that is the process of selecting and giving priority to the processes in a manufacturing system. Zhou et al., (2007) provide a research review on analyzing electricity markets and modeling. They investigate several agent-based tools on electricity markets. Then they provide a comparison on different tools.

There are two main groups of applications of ABSs in supply chain management in the literature. The first approach referring to strategic levels in supply chain management. For instance, Giannakis & Louis (2011) develop an agent-based framework for supply chain risk management and Kaihara (2003) provides a multi-agents approach to solve product allocation problems in supply chain with concentration on a virtual market. The second group of ABS researches in supply chain management is in operational and tactical levels including resource allocation and ordering problems where agents represents members of supply chain and they interact with each other.

A practical collaboration framework using MASs, is presented by Ahn & Lee (2004) for supply chain management. They formed dynamic information networks of order planning according to synchronized estimation of market demands. This framework employs ABS approach to find the most appropriate suppliers after analyzing the data.

(Pan et al., 2009) apply agent-based simulation in facshion industry while the study of Lin & Lin (2007) proposes an agent-based approach for an order fulfillment problem. Another study tries to solve a production–distribution planning problem using agent-based approaches, then they compare their results with the achieved results from GA from a DSS (Kazemi & Zarandi, 2008). Liang & Huang (2006) propose an agent-based approach for simulating a supply chain, in this simulation each agent represents an actor in the supply chain. In this simulation, agents are responsible to control the inventory and reduce the total cost of them in supply chain. To reduce the total costs, agents are sharing information with each other and they benefit from the forecasting features in ABM. To forecast the demand in this problem, a genetic algorithm and an ordering quantity is used in each level. The results from this research claim that total cost drops and the ordering variation becomes less fluctuated.

The ability of ABSs in supply chain problems is tested through the study of (Karageorgos et al. (2003), when they checked the ability of ABS in a case study of production planning in a virtual manufacturing company. In this study, the enterprise and its relation to the other members of supply chain is studies.

Forget et al., (2008) implement a hybrid of ABS and a classical operational research approach to propose a DSS for in forest industry’s supply chain. The same approach is used by Frayret et al., (2007). Study of Wang et al., (2013) demonstrates that ABS are able to produce a DSS for evaluating supply chain formation alternatives in an argumentation interaction protocol. Other studies try to solve different supply chain configuration problems such as resource allocating (Akanle & Zhang, 2008; Mele, Guillén, Espuna, & Puigjaner, 2007).

An analysis of different agent-based approaches in supply chain management is done by Caridi & Cavalieri (2004). They address the shortage of real world applications of agent-based approaches and low maturity of these technologies as a drawback in this field of study.

2.2.1. Computer Simulation in Healthcare Industry

Computer-based simulations are able to answer to numerous research questions in healthcare industry. In the process of answering these questions, the simulation systems provide explanations on different aspects of healthcare industry. The abilities of computer simulations in recent decades made them a useful instrument to understand any complex and dynamic system including healthcare industry. A variety of questions that can been answered by using computer simulations are mentioned in a review from Fone et al., (2003) and Gul & Guneri (2015) more specifically provide a review on the abilities of computer simulations in EDs. These reviews also discuss how computer simulations deal with stochastic factors in the healthcare industry. Moreover, they discuss how computer simulations provide valuable evidences in these researches.

Computer simulations can be categorized in different groups by using different criteria. One of these categorize divide these studies into discrete event simulation (DES) and agent-based simulations (ABS). Each category has their own advantages and disadvantages and both are used in healthcare industry. For instance, study of Duguay & Chetouane (2007) models an ED using DES and their results show that DES tool can effectively simulate the complexity of healthcare industry in an ED. They also recommend that a combination of total quality management and continuous improvement techniques can be useful when they are working in collaboration with DES. To improve the performance of their case study, first they try to evaluate the current condition of the ED through data collection and study different variables including number of nurses, number of doctors, number of beds etc. Afterwards, by analyzing the waiting times and different scenarios in terms of number of staff in each section and also varying number of examination rooms in the predefined budget limits they were able to improve the performance of an ED.

One of the most common software in DES is ARENA simulation software that is vastly used in different fields of DES. Kumar & Mo (2010) produce a bed forecasting model using Arena 10.0 to evaluate the occupancy level of beds for three different types of patients in three different wards. The daily visits, capacity of the hospital, number of different types of patients were collected through a data collection process in a hospital and their ALOS that happened during a year. The achieved results show that the simulation is able to predict the occupancy of beds in the hospital with an error rate of 0.05 when the prediction happens a week in advance. Zeinali et al. (2015) also used simulation package Arena 14.0 to simulate the patients flow in an ED. The achieved results show that the total average waiting times reduce from 44 minutes to 23 minutes after applying an optimization approach. Study of Zeng et al. (2012) uses a simulation approach applying by Simul8 to evaluate the quality of care in healthcare industry in term of patient elopement, waiting times and LOS to provide a continuous improvement tool in hospitals. The results from the paper shows an improvement in resource planning of the case study.

The benefits of using DES in healthcare industry is reviewed in the study of Jacobson et al. (2006). This paper shows that DESs are useful tools to optimize the configurations of system; in fact, these tools make the decision makers in healthcare able to make better decisions. One of the benefits of using DESs in healthcare industry that made these tools more acceptable for decision makers in healthcare industry is their ability to incorporate multiple performance measures in healthcare industry to help the decision makers having better understanding of the input, output and the relationships inside the system.

Another review of applications of DES in healthcare industry is done by Jun et al. (1999). Their literature review reports an improvement in patient flow as well as waiting time and distributing patient demand. The study also shows that the improvement in patient flow comes from the reduction in patients waiting time in systems.

A recent literature review from Gul & Guneri (2015) study both DES and ABS studies in healthcare industry. They show that although DES tools are the most common used tools in simulation of healthcare, after 2011 an increase in using ABS as a tool to simulate EDs is observed. Pan et al. (2007) provide an agent-based framework for simulating social behaviors and human behaviors during emergency evacuations. Liu et al. (2014) provide a generalized ABM to simulate EDs. Their model was implemented using Netlogo platform and their results show that the proposed approach can be apply to different EDs after some modifications.

Transparent models let us to see how the model is built (Eddy et al., 2012). The importance of these models are investigated by Eddy et al (2012), this models are valid in reproducing reality to become successful within the healthcare industry. Transparent models are easier to be validated and verified. Moreover, they are easy to be re-produce by others because unlike black box systems, their mechanism can be seen. The transparent models have the ability to simulate sources with details and as close as possible to the real case outputs.

There are also many simulation studies that have been applied to the emergency department such as studies done by Miller et al. (2004), Samaha et al. (2003), and Blasak et al. (2003). Table 2-1 shows the summary of the most used simulation platforms during normal and disaster conditions provided from the Winter Simulation Conference (WSC) paper archive. These data are exctracted from Gul & Guneri (2015). It can be seen most of platforms are suitable only for DES. For instance, Arena which is the most used software in this are is a DES simulation software. This litrature review listed only three ABS papers using ABS and five papers using ABS and another methodology.

Table 2-1. Simulations platforms in emergency department simulation.

No	Arena	Simul8	Netlogo	AnyLogic	MedModel	Flexim
1	(Wang et al., 2013)	(Weng et al., 2011)	(Cabrera et al., 2012)	(Day et al., 2012)	(Batarseh et al., 2013)	(Holm & Dahl, 2009)
2	(Eskandari et al., 2011)	(Davies, 2007)	(Taboada et al., 2011)	-	(Spedding, 2008)	(Holm & Dahl, 2010)
3	(Sengupta et al., 2011)	(Brenner et al., 2010)	-	-	(Ruohonen et al., 2006)	(Patvivatsiri, 2006)
4	(Kolb et al., 2007)	(Zeng et al., 2012)	-	-	(Kirtland et al., 1995)	-
5	(Medeiros et al., 2008)	(Wang et al., 2012)		-	(McGuire, 1994)	-
6	(Rico et al., 2007)	(Ajami et al., 2012)	-	-	(Powell et al., 2007)	-
7	(Park et al., 2008)	-	-	-	(Khare et al., 2009)	-
8	(Joshi, 2008)	-	-	-	-	-
9	(Konrad et al., 2013)	-	-	-	-	-
10	(Rado et al., 2014)	-	-	-	-	-

Table 2-2 divided the literature review based on their countries. (Gul & Guneri, 2015) show that most of studies on EDs are from developed countries. For instance, in their study, USA with 52 papers is first and UK and Canada with 14 and 5 papers respectively are second and third. While all other 22 countries contribute in 35 papers on simulation in EDs. They did not cited any study from Brazil in this field.

Table 2.2. Simulation based researchers in ED from different countries (part 1).

NO	Country	Researches in Emergency departments								
1	USA	(Connelly & Bair, 2004)	(Khare et al., 2009)	(Hoot et al., 2008)	(Kolker, 2008)	(Joshi, 2008)	(Powell et al., 2007)	(Peck & Kim, 2010)	(Zeng et al., 2012)	(Chockalingam, et al., 2010)
2	UK	(Maull et al., 2009)	(Izady & Worthington, 2012)	(Aboukanda & Latif, 2013)	(Bowers et al., 2009)	(Eatock et al., 2011)	(Mustafee et al., 2013)	(Fletcher et al., 2016)	(Mould et al., 2016)	(Bowers & Mould, 2013)
3	Iran	(Eskandari et al., 2011)	(Ajami et al., 2012)	(Azadeh et al., 2013)	-	-	-	-	-	-
4	Jordan	(Mandahawi et al., 2010)	(Al-Refaie et al., 2014)	-	-	-	-	-	-	-
5	France	(Wang et al., 2013)	(Kadri, Chaabane, & Tahon, 2014)	-	-	-	-	-	-	-
6	Italy	(Rado et al., 2014)	(Fruggiero et al., 2008)	-	-	-	-	-	-	-
7	Singapore	(Choon et al., 2014)	(Spedding, 2008)	-	-	-	-	-	-	-
8	Sweden	(Setijono et al., 2010)	-	-	-	-	-	-	-	-
9	Australia	(Diefenbach & Kozan, 2011)	-	-	-	-	-	-	-	-

Table 2.3.Simulation based researchers in ED from different countries (Part 2).

No	Country	Researches in Emergency departments	
1	UAE	(Al-Kattan, 2009)	-
2	Tunisia	(Jerbi & Kamoun, 2009)	-
3	Canada	(Duguay & Chetouane, 2007	(Khurma, Bacioiu, & Pasek, 2008)
4	Ireland	(Abo-Hamad & Arisha, 2013)	(Ismail, Abo-Hamad, & Arisha, 2010)
5	Germany	(Kolb et al., 2007)	-
6	Taiwan	(Yeh & Lin, 2007)	-
7	Turkey	(Gul & Guneri, 2012)	-
8	Norway	(Holm & Dahl, 2009)	(Holm & Dahl, 2010)
9	Spain	(Cabrera et al., 2012)	(Taboada et al., 2011)
10	Kuwait	(Ahmed & Alkhamis, 2009)	-
11	Chile	(Baesler et al., 2003)	-
12	Japan	(Takakuwa & Shiozaki, 2004)	-
13	Finland	(Ruohonen et al., 2006)	-
14	China	(Cao & Huang, 2012)	-

2.3. Optimization

Computer-based simlaions are tools to translate a real word system to a computer program to make us able to see the responses of the system to the changes. Nowadays computer-based simuations are widely used in different fields of study including supply chain, manufacturing, designe of heat exchangers, finance etc. (Fu & Hu, 1995; Gurkan, Ozge, & Robinson, 1994; Kim & Ding, 2005; Plambeck, Fu, Robinson, & Suri, 1993; Semini, Fauske, & Strandhagen, 2006). The reason behind making compter-based simulations is to study the behavior of the systems and eventualy improve their performances by finding a (near) optimum parameters setting for the system. Even if we have a very good simulation of a system, still finding the best configuration is not an easy task. Especially when the simulation is complex and we have more decision variables. One of the most common approaches to do a simulation and find the better configuration is simulation-based optimization (Banks, 1998; Fu, 2002; Fu, Glover, & April, 2005; Gosavi, 2003; Kim & Ding, 2005; Ruszczyński & Shapiro, 2003). Simulation-based optimizations are integrated systems that apply optimization techniques through simuations. In these systems, an objective function is an output of a simulation system. In fact, the decision variables are used as input of the simulation system, then the output of simulation system is used as input of optimization model to find the best configuration. When our simulation system is complex, we have a complex and computationally expensive objective function therefore, evaluating the obective function imay be difficult. Moreover, in these problems the objective function might be inaacurate and that makes the problem even more complex.

Most of EAs are inspired by nature such as GA that is inspired by natural selection and simulated annealing that is inspired by annealing in metallurgy. Unlike other EA, Imperialist Competitive Algorithm (ICA) was introduced by Atashpaz-Gargari & Lucas, (2007) inspired by social-political evolution of mankind; the behavior of imperialist countries looking for more power and competing with other empires to take possession of more colonies. The population and optimization process is similar to genetic algorithm (GA) with the difference that the crossover and mutation operators are replaced by the assimilation and revolution throughout the evolution process.

ICA has shown great performance in finding global optima in numerous famous benchmarks from the literature in engineering and other fields of study. In many cases ICA shows better performance when the results are compared to other well-known algorithms such as GA. The applications of ICA can be found in diverse engineering applications such as single machine scheduling problems (Yousefi & Yusuff, 2013), optimization in heat exchangers (Yousefi, Yousefi, & Darus, 2012), industrial engineering, computer sciences, power systems and others.

2.4. Emergency department

The study of Han et al. (2007) proved that an increase in number of beds in an ED does not affect the ambulance diversion significantly. The same results are reported about the correlation between total length of stay and bed capacity of ED. Their results did not prove the assumption of bed capacity being bottleneck in hospital.

The effects of occupancy in hospital and its relation with length of stay in ED and total number of discharged patients are studied in Forster et al. (2003). Their study was conducted in a teaching hospital with 500 beds capacity to study the behavior of the hospital focusing on occupancy and LOS. They proved that increasing in occupancy of hospitals is the main factor in increasing ALOS. They also showed that a 90% occupancy of beds in hospital will increase the LOS in ED therefore, this factor was considered as an important factor in overcrowding in ED. They also proved that the increasing in availability of beds in hospital may help reduce the LOS. Although they do not have many evidences about that.

Forster et al. (2003) studied the effects of hospital occupancy, on emergency department length of stays and patient disposition. They conducted an observational study of a 500 beds acute care teaching hospital. They showed that increased hospital occupancy seemed to be a major indicator of increased ED length of stay (LOS) for admitted patients. A threshold of 90% bed occupancy appeared to indicate extensive increase in ED length of stay which is believed to be an important determinant of ED overcrowding when the occupancy is limited to 90%. Although there is little data verifying the claim. they suggested increasing hospital bed availability might contribute to less ED overcrowding especially when at the 90% bed occupancy threshold.

Gunal (2012) provides a guideline for building simulation models in for hospitals. Three well-known simulation approaches including discrete event simulation, system dynamics and agent-based simulation are considered. The study tries to highlight the important areas of research in hospital modeling. The study points that level of generality is a significant in determining the reusability of simulations. It also proves that ABS is a model contains of self-deciding and it can be useful in these types of studies in hospitals. This guide might be a good start for beginners in modeling in healthcare industry.

How overcrowding in ED and ambulance diversion does effect the boarding times of patients who are waiting to be attended in a hospital? The study of Olshaker & Rathlev (2006) tries to answer this question. They showed that the inability to receive patients in ED is the main of overcrowding in ED.

Zeinali et al. (2015) tries to solve a resource planning problem in an ED. They provide a discrete event simulation sing Arena to simulate the routine of the ED and total waiting time was selected as a factor to evaluate the performance of the simulation. After verifying and validating the model, the proposed simulation approach is used to reduce the total waiting time by considering two constraints of budget and capacity. The experimental results show an increase of 48% in total waiting time after applying new resource planning.

Another research proposes a conceptual model of an ED and describe that as an acute system that provide treatments in an unscheduled manner Asplin et al. (2003). The computational results from that study is more focused on the output component and boarding. They also investigated one of the most well-known reasons of overcrowding in EDs (the inability to send admitted patients to inpatient beds). This is one of the reasons that avoid the system to admit any new patient. Another factors of having inpatient boarding in ED are listed in this study as follows: delay in cleaning the facility and beds after being used, inflexible staffing and delays in discharge the patients who are ready to be discharged.

A literature review on influence of reducing crowding in EDs by doing crowding initiatives such as vertical patient flow is done by Liu et al. (2013). Vertical patient flow is a method which is used for managing and evaluating patients when we do not have access to an ED room. They suggested that examining the effects of crowding initiatives to improve performance of ED (ALOS, waiting time, satisfaction etc.) as remarkable topic for future study.

The complexity of EDs and the related issues on overcrowding in these departments and the effects overcrowding on different factors including patient risk, long patient waiting time, patients' dissatisfaction, productivity of staff are studied (Derlet & Richards, 2000). This study pointed at lack of beds in hospital for patient being attended as one of the main reason of overcrowding in this sector. The effects of overcrowding on the quality of healthcare is discussed also with useful details in this research. A common problem in all EDs is introduced as long boarding time when patients have to wait for beds to be available.

The influence of crowding in EDs when more beds are added to ED is studies by Khare et al. (2009) to check if the increase in ED beds will cause a reduction in total boarding time for admitted patients. Their research proves that improving in the rate of discharging patients from ED decreases the total LOS in ED. The other finding of this study shows that the main bottleneck in EDs that make them overcrowded is admitted patient departure from hospitals.

2.4.1 Optimization in Emergency Department

Computer based simulation tools are well-known models to study the behavior of hospitals and in particular EDs and their sub-systems and processes. In order to do these analyzes, in most cases they compare the results of several scenarios that they are called as "what-if" scenarios. "What if" scenarios make the decision-makers able to know reactions of the system to changes. Study of Seila & Brailsford (2009) investigates the advantages and disadvantages as well as threats and opportunities in computer simulations in healthcare industry. Their study shows that although it has been long time from the first applications of simulation in healthcare industry, in last 40 years of history of optimization in healthcare industry, the optimizations in some cases are working manually. Cardoen et al. (2010) show that most of studies in this field of study are based on discrete event simulation models and combining them with scenario analysis. The scenario analysis is used as an optimization tool and it works by running the same simulation model with different configurations. Although, obviously this approach cannot be accepted as an optimization approach, it might be helpful. They also categorize the studies based on the optimization approaches that they applied.

The first step in any optimization process is to define the problem. An error in definition of a problem in optimization, lead the decision makers to be far from their objective. Defining a problem contains of setting decision variables and objective functions and defining the constraints. The study of Hachicha et al. (2010) provides some examples of applications of simulation optimization in manufacturing systems, logistics and inventory models.

The combinations of simulation approaches with optimization techniques have been used more in recent years to find near-optimum values of resources and other decision variables in different industries including healthcare industry and emergency departments (Ahalt, Argon, Ziya, Strickler, & Mehrotra, 2016; Ghanes et al., 2015; Gul & Guneri, 2015).

Ahmed & Alkhamis (2009) provide a discrete event simulation model in combination with an optimization technique in order to making a decision support system for an emergency department in Kuwait. The achieved results show that the new approach was able to reduce the total waiting time in the ED and increase the total number of discharged patients in a day. Their results show an increase of 28% in number of discharged patients in a day and a reduction of 40% in total waiting time.

Taboada et al. (2011) and Cabrera et al. (2011) provide a pure agent-based simulation decision support system in an emergency department in Spain, using exhaustive search. Yeh & Lin (2007) applied a computer simulation model and genetic algorithm to improve nurse schedules in an emergency department in Taiwan. Their reported results show that a 43.47 and 43.42% reductions in queue times on average.

2.5. Metamodeling

Although optimization-simulation methods have been successfully applied in different ED-related problems, reviewing the past 10 years' worth of literature shows that a common problem with these methods is that they are computationally expensive to explore the entire search space in real-life optimization problems. In this thesis, an attempt is made to tackle this problem by applying a robust approximation model to find relationships between the inputs and outputs of the proposed DSS and make the process as fast as possible while maintaining reliable approximation. This type of relationship between inputs and outputs is called a "metamodel" (Kleijnen, 1975).

Metamodels enable researchers to obtain reliable approximate model outputs without running expensive and time-consuming computer simulations. Therefore, the process of model optimization can take less computation time and cost. Simulation-based metamodels enable users to employ these tools in crisis decision-making when a case is serious and there is only a very short response time to manage it (Barton & Meckesheimer, 2006; Kleijnen & Sargent, 2000).

Machine learning methods have proven to be efficient in finding the nonlinear relation between the inputs and outputs of simulation models. While machine learning, and in particular neural networks, have been successfully employed for constructing metamodels in recent years, there has not been much effort on systematically increasing metamodel efficiency. The literature has shown that the performance of neural network-based metamodels (or predictors in the case of forecasting problems) can be improved, in some cases drastically, by utilizing an ensemble of different metamodels based on their individual performances (Hansen & Salamon, 1990). Nevertheless, the potential of ensemble metamodeling has not been explored for the problem at hand.

Chapter 3
Research Methodology

3.1. Introduction

In this chapter, the research methodology to achieve the mentioned objectives of the study in Chapter 1 is presented. Furthermore, the real world case study and data collection are explained. The used ABS in this study and the behavior of agents as well as the interactions between agents are presented. Then a proposed metamodel approach and the optimization approaches (GA and PSO) are discussed.

3.2. Simulation Methods

Simulation is one of the most common tools in operations research to investigate different alternatives in any manufacturing system. The history of simulation is back to Buffon's "needle experiment" in 1777 (Goldsman, Nance, & Wilson, 2009). After advent of computer, different methods of computer-based simulation including discrete-event simulations (DES) and agent-based simulations (ABS) were introduced. Each of these popular methods have their own advantages and disadvantages. Both aid decision makers to understand manufacturing and service systems to improve their performances. They are able to provide an analyzing of the current situation of the system as well as behavior of systems in different situations.

Although DES is mostly useful to simulate the flow of patients in an ED and find bottlenecks in a short time, it is so limited in simulating human behavior and interaction between different components of the simulation. For instance, in an ED most of agents are human and they interact with each other and they learn from their experiences as well as experience of the ones that they are in contact with. The process of treatment of a patient in an ED is nothing but the results of interactions between an agent (patient) with other agents (Receptionist, Doctor, Nurse, etc). In fact, DES is simple and limited in decision-making. Which means that in a DES the possible path of the entity (components of a DES system) is pre-determined (Gunal & Pidd, 2006). For this reason, an ABS approach was chosen in this study. In next section, the proposed ABS approach and its ability to simulate human behavior will be explained.

3.2.1. Agent based simulation

An ABS system contains a group of autonomous individuals that interact with each other and make decisions independently. Each individual is known as an agent. Figure 3-1 shows a simple example of an ABS. A typical ABS consists of three main components:

1) Agents and their characteristics and behaviors.
2) Relationships between agents and their interactions.
3) Environment.

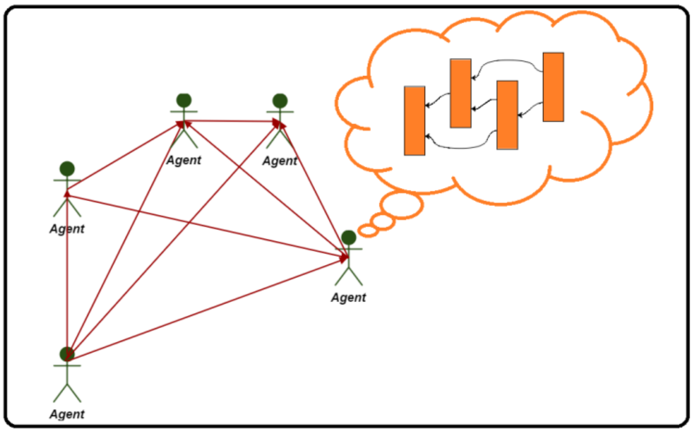

Figure 3-1. Agent based simulation system.

Each simulation might have various types of agents and different amount of number from each agent type. In next step, different agent type that are used in our study will be introduced.

3.2.1.1. Agents type

After study the behavior of ED as a system and study the relevant literature, the following agents were selected for this simulation:

Patients: Patient agents are patients who go to ED to be treated. Patient agents are created with a non-homogenous Poisson process to go to the ED and wait for a treatment. Each patient agent has the following possible behavior in the process of the simulation:

- Waiting for a treatment: Patient agents will wait until the relevant caregiver will be available.

- Receiving service (treatment): Patient agents can receive a service or treatment.

- Making decision to stay in ED or leave: In each step of the treatment, patient agents have the ability to make decision whether they continue the process or leave the ED because of long LOS.

- Worsening or improvement in health condition: The health condition of patients can be improved in case of receiving treatment or worsen in case of not receiving proper treatment.

- Moving to different sections: Patients are able to go to different sections (admission, triage room, x-ray or laboratory) of ED to receive the service or treatment.

- Dying: If patients do not receive a proper treatment, they might die in the ED.

Doctors: Doctor agents are one of the most important caregivers in an ED that are able to do the following actions:

- Waiting for a patient.

- Giving service.

- Moving to different sections.

- Participating in group decision-making: In next sections the group decision-making process that doctors participate in that will be discussed in details.

- Categorizing patients in triage room: The categorizing process in triage room will be explained later in this chapter.

- Decreasing performance: Doctors are not as productive as of when they begin their shift.

Laboratory technicians: Laboratory technician agents are in charge of x-ray and laboratory examinations and they are able to do the following actions:

- Waiting for a patient.

- Giving service.

- Participating in group decision-making.

- Decreasing performance: Technicians are not as productive as of when they begin their shift.

Nurses: Nurse agents are another type of caregivers that they also have the supervisory role. The following actions are introduced for a nurse agent:

- Waiting for a patient.

- Giving service.

- Attending in group decision-making.

- Categorizing patients in triage room.

- Moving to different sections.

- Decreasing performance: Nurses are not as productive as of when they begin their shift.

Nurse Technician: Nurse Technicians are also able to do the following actions:

- Waiting for a service.

- Giving service.

- Decreasing performance: Nurse Technicians are not as productive as of when they begin their shift.

Beds: Beds are among the simplest agents. They have two main behaviors as follow:

- Changing the status from occupied to free and reverse versa.

- Changing the status from clean to dirty and revers versa.

3.2.1.3. Communication between agents

Communication is an output for an agent that produce it and it is an input for an agent that receives it. An agent might change its state after a communication or it might continue with the same state. In this study, there are three types of communications between agents (Figure 3-2).

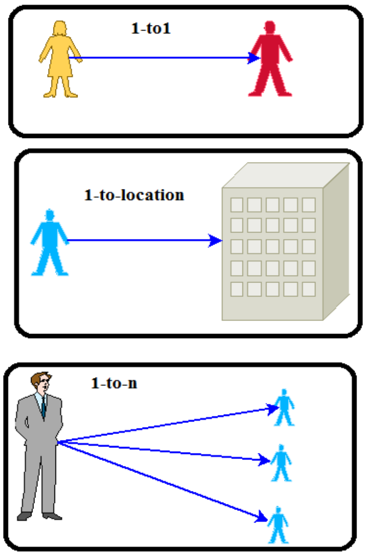

Figure 3-2. Different types of agents communications.

- One to one communication: this type of communication happens between two individual agents that means one agent delivers a message to another agent. This message can change the state of the receiver agent or not. For instance, when a patient goes to a triage room a message goes to a triage nurse and change its state from "waiting for a patient" to "giving service". This type of communication has one sender and one receiver.

- One to n communication: In this type of communications, there is only one sender to send a similar message to group of agents. When a nurse informs a group of patients to go to another section, the type of communication is one to n.

- One to location communication: This type of communication happens when an agent sends a message to all agents in a specific location. For instance, when a nurse informs all of patients in waiting room that there is no available bed. This message is sent by a single sender and will be received by a group of agents who are in that waiting room (Taboada et al., 2011).

Another type of communication that can be classified under "one to location communication" is when a message is transferred to a place and for a period of time stay there. Therefore, any agent that goes to that location during the time will receive the message.

3.2.3. Environment

In agent based systems, in both micro or macro level, agents are interacting in a shared environment that has the role of agent diversity of behavior. Agents show different behavior because of their environment. Figure 3-3 shows the environment in this ABS.

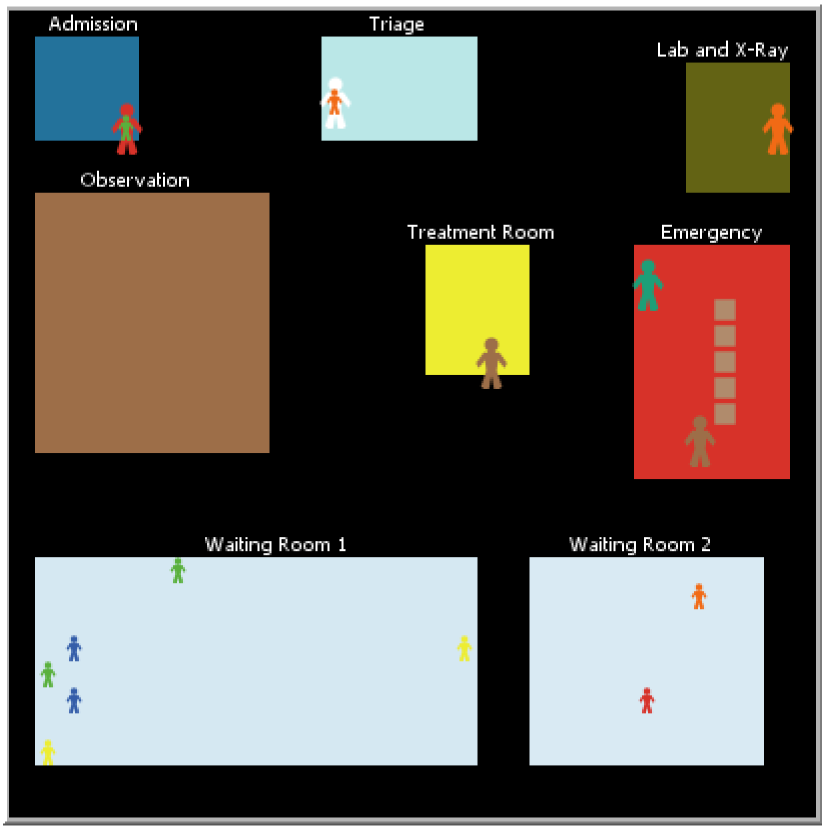

Figure 3-3. Environment of an agent based simulation system.

3.3. Self-organizing approach

The self-organizing approach in this study is the group decision making (Herrera-Viedma, Martinez, Mata, & Chiclana, 2005) happens with the vote from all the staff in the ED. In this problem, we have m decision makers: doctors, nurses, technicians etc. that are represented by $D_1, \ldots, D_l$, and there are n available scenarios (each scenario can be described as a resource plan for ED) $A_1, \ldots, A_n$ and m different criteria $A_1, \ldots, A_n$ (waiting time in room 1 or 2, LOS, etc.). a_{ij}^k is the result of the assessment of staff for scenario A_i, considering criteria C_i. Decision makers have different preference on different criteria based on the sector that they are working. The weight given by decision makers D_k at criteria C_i , $i = 1, \dots, m; k = 1, \dots, l$ is always a non-negative number $w_i^k \geq 0$. Decision makers give different weights to each criteria based on their knowledge and duty.

The voting power of D_k for weighing on criterion C_i is shown with $V\ (w)\ _i^k$. In the same manner, the voting power of D_k for scoring on criterion C_i shown as $V\ (q)\ _i^k$ where $i = 1, \dots, m$ and $k = 1, \dots, l$. The group score for scenario A_j is calculated as follow:

Firstly, the individual preference for each criterion C_i is aggregated into group weights W_i :

$$W_i = \frac{\sum_{k=1}^{l} V(W)_i^k \, W_i^k}{\sum_{k=1}^{l} V(W)_i^k} \ , \quad i = 1, \dots, m \qquad (1)$$

Then, the group score Q_{ij} of scenario A_i based on criterion C_i is calculated as follow:

$$Q_{ij} = \frac{\sum_{k=1}^{l} V(q)_i^k \ a_{ij}^k}{\sum_{k=1}^{l} V(q)_i^k} \ , \quad i = 1, \dots, m, j = 1, \dots, n \qquad (2)$$

The weighted mean of the aggregated qualification values with the aggregated weights is the group utility U_j of A_j that is as follow:

$$U_j = \frac{\sum_{i=1}^{m} W_i \ \ Q_{ij}}{\sum_{i=1}^{m} W_i} \ , \quad j = 1, \dots, n \qquad (3)$$

In this study, a simple blackboard system is implemented for interactions between agents in general and specifically for decision making. A blackboard system contains a shared database area for the whole ABS that is surrounded by the information from agents (Figure 3-4). All agents are able to read and write to this blackboard. Therefore, any change at each step of simulation will be written there and all agents will be aware of that to make their decision for next steps based on that. Blackboard systems are working in interaction with the simulation platforms as a black box (Engelmore & Morgan, 1988).

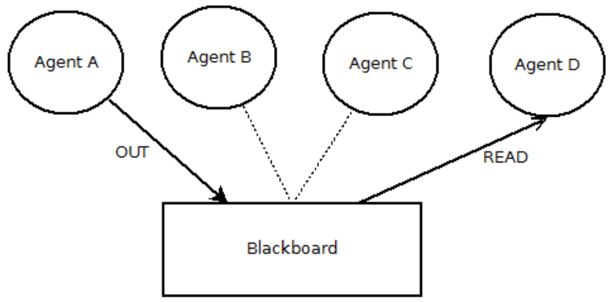

Figure 3-4. An example of simple blackboard system in ABS.

The blackboard system helps the agents to be updated about the number of patients who are waiting for a service in each section also the patient with least occupancy rate can be easily selected in the system to send it to the other section. Occupancy rate can be defined as a ratio of the time that a staff is providing service to the total amount of time.

3.4. Cellular automata

In this study, in order to simulate the human behavior different approaches were used. One the most useful approaches in simulation queues is cellular automata (CA). Although the first applications of CA were in early 1950s in biological systems, the expansion of CA were introduced in “A New Kind of Science” of Wolfarm in early 1980s (Wolfram, 1983). CA were mathematical methods of representing complex models when the interactions between agents is based on local rules. Wolfarm (1983) used a simple one-dimensional CA that each cell has one of the options of “ON” or “OFF” with 4 neighbors, one at right, one at left, one in front and one at the back side. Although various applications of CA can be found in queuing of different systems (Sankaranarayanan, Delgado, van Ackere, & Larsen, 2014), to the best of our knowledge this is the first application of CA in simulation of at hand simulation.

In this study, a one-dimensional CA with three behavioral parameters (a, b) is applied. Generally, a ring structure is mostly used in queuing problems and they consider that agents have one agent in front and one at back. In our study, the agents in most cases instead of waiting in a queue they wait in a waiting room for their number to be called.

Therefore, to have a better approach to simulate the behavior of agents and make the calculations simple, we assume that each agent at maximum can have four agents around.

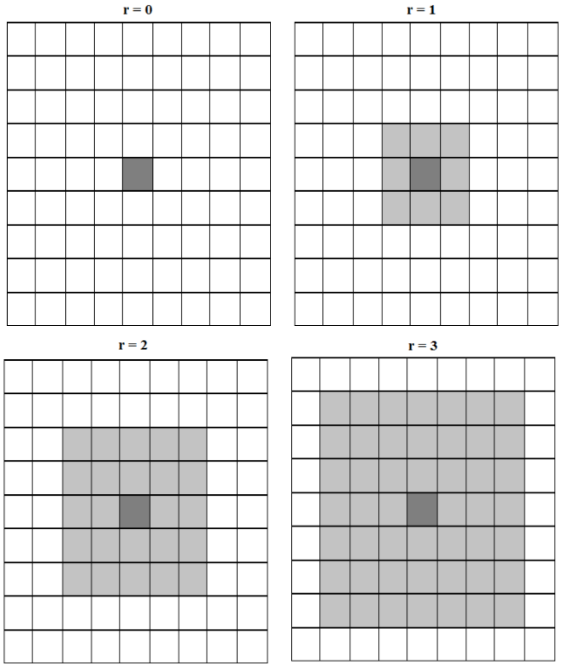

Figure 3-5. Moore neighborhood for r = 0, r =1, r = 2 and r = 3.

In general, there are two famous methods to define the neighborhood of an agent in CA. The first approach called Moore Neighborhood and as it can be seen in Figure 3-5 it is a square shape. The other approach is Neumann neighborhood for that is diamond shape and it can be seen in Figure 3-6 for the neighborhood ranges of 0, 1, 2 and 3. CA divides the environment into cells therefore, the neighborhood of each cell at $(x_{0\,,}\ y_0)$ when the range of neighborhood is represented by r is as follow:

$$N^M_{(x_0\,,\,y_0)} = \{(x,y) \colon |x - x_0\,| \leq r\,\}$$
$$N^M_{(x_0\,,\,y_0)} = \{(x,y) \colon |y - y_0\,| \leq r\,\}$$

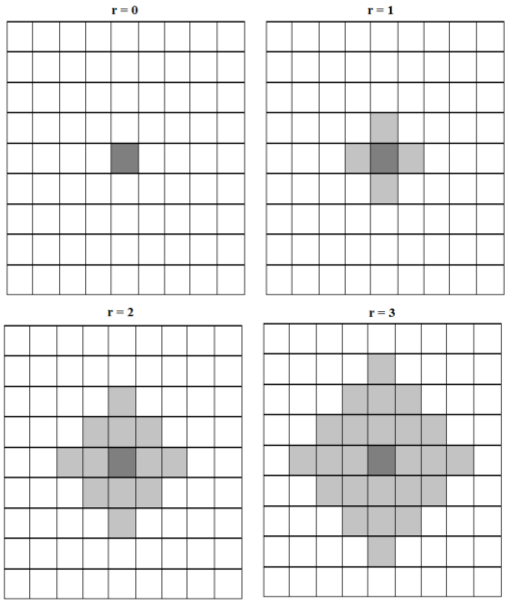

Figure 3-6. Neumann neighborhood for r =0, r=1, r=2 and r=3.

As it was mentioned earlier, in this CA, there are three behavioral parameters (a, b) that make the agent to decide whether keep waiting in waiting room or leave the ED. These parameters are as follows:

a: Agent's memory, that is the time that agent waits in ED.
b: Neighbors' experience.

In this study, first we extracted estimated tolerance time from literature (Shaikh, Jerrard, Witting, Winters, & Brodeur, 2012). They conducted their study during March to July 2010 and studied the behavior of 375 participants considering their age, gender, acuity level, race and insurance status. Analyzing the data shows that 51% of patients wait up to 120 minutes to leave the ED, 17% of them wait 120 minutes to 480 minutes, and 32% of patients wait indefinitely to receive a treatment. In our simulation, patients will not leave the ED only based on their memory; they also have a look at their neighbors. Therefore, we call "a" as tolerance time. When an agent reach to its tolerance time, starts communicating with the agents in its neighborhood (if any) and remembering the whole process. When patients reach to their tolerance time and they had no neighbors since they came to ED, they leave the ED on their tolerance time. In the model, it shows with $N = 0$.

Patients with neighbors $N \neq 0$ will check their memory to see if $N_{delayed} \geq N_{normal}$ the patient will leave the ED. In a case that $N_{delayed} < N_{normal}$ the patient will wait for T minutes more to receive the treatment.

$$T = 0.10 * ToleranceTime$$

If patients do not receive treatment after the additional time, they will leave the ED. Figure 3-7 demonstrates the simulation framework of this study including the material, applied methodologies and results.

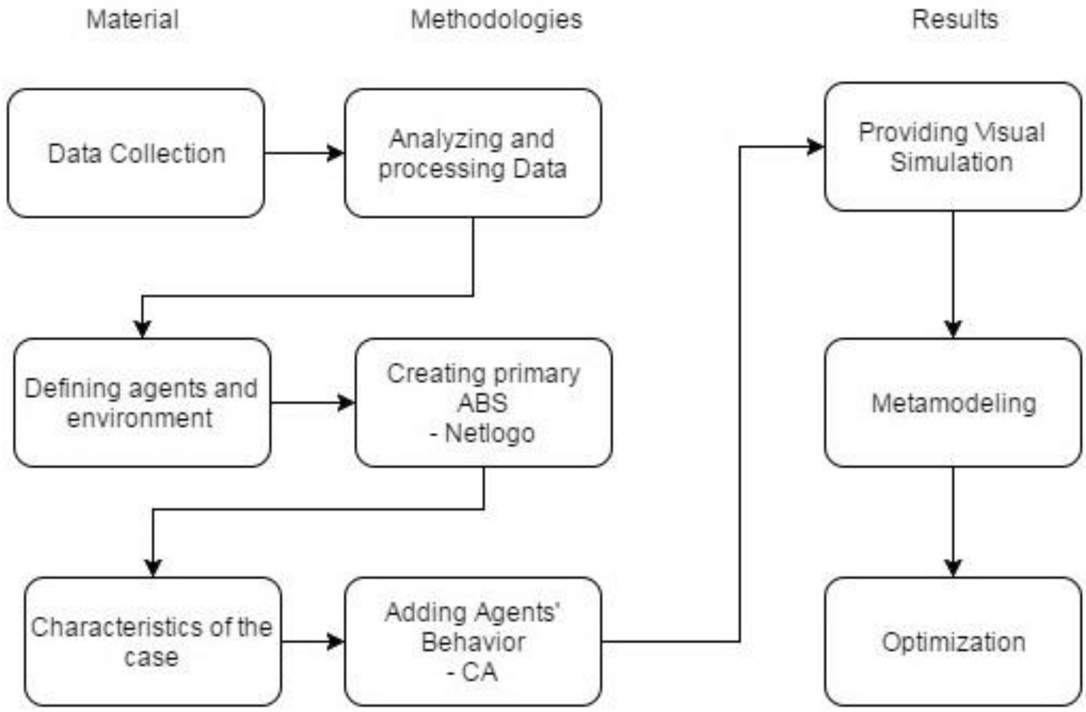

Figure 3-7. Simulation Framework.

3.5. Structural Model

In order to make a reliable ED simulation model, data collection is needed. The main data collection elements in this simulation are as follows: the amount of time each service takes (e.g. admission, triage, laboratory, etc.), patient arrival rate and the number of each type of patients in the ED. From January 2016 to May 2016 around 24000 data were collected and analyzed to achieve proper model inputs. One-fourth of the gathered data were used for model validation and 75% served as input to create the model. The patients flow in an HRTN can be seen in Figure 3-8. Patients arrive by walk or with an ambulance to the admission. Then, patients wait until they will be attended by a receptionist in admission to register their personal information. This step can be skipped in case that the patient is in police custody and the patient directly goes to the triage room. The process of arriving patients to the ED is a non-homogenous Poisson process that is shown in Figure 3-9 where the λ(t) is the estimated function of patient arrival per hour.

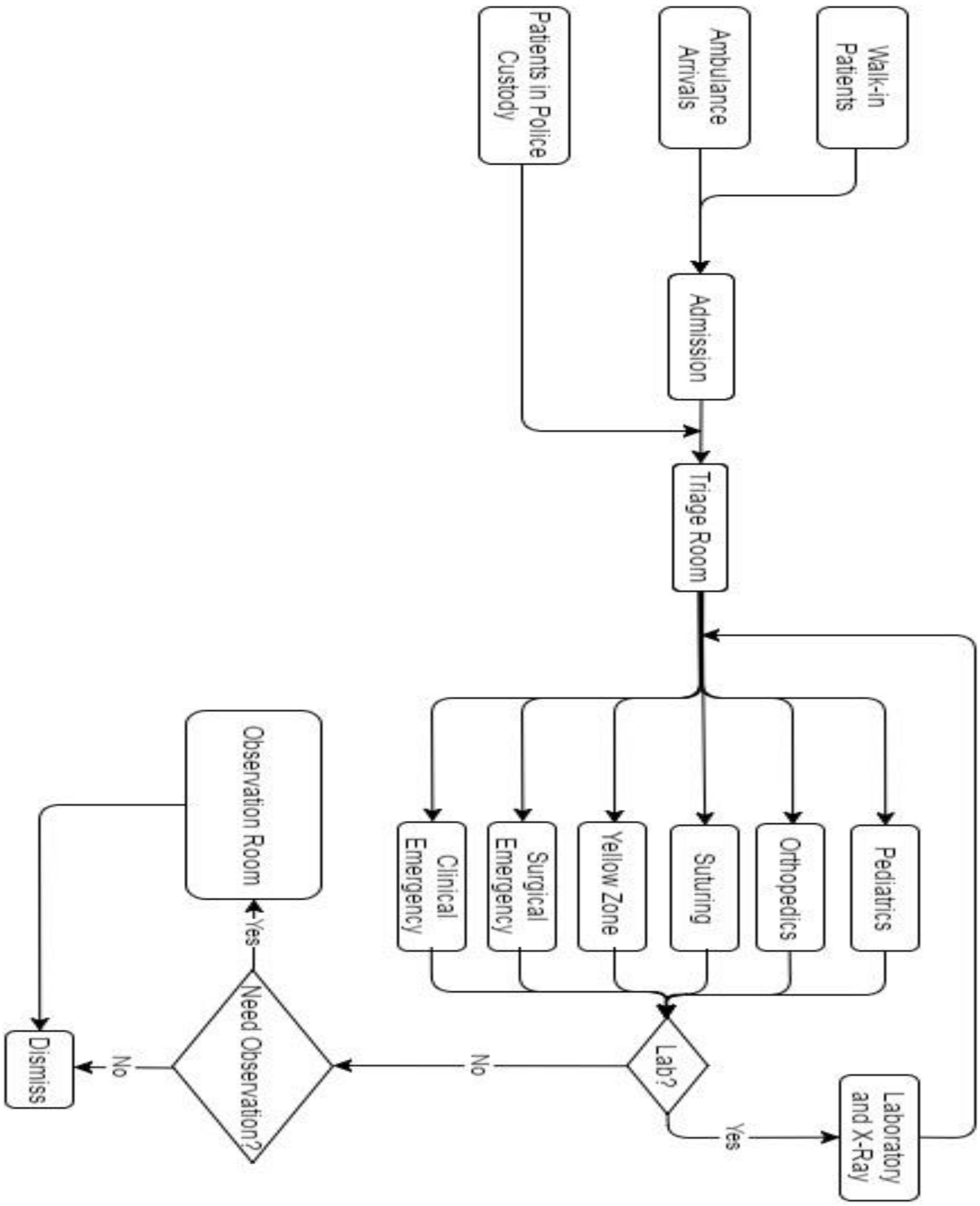

Figure 3-8. Patient flow in Risoleta Tolentino Neves hospital.

Data analysis showed that 44% of patients go to the yellow zone, 30% go to the orthopedics section, 7.8% go to pediatrics and 7.0% go to surgical emergency, while the suturing section and clinical emergency rates are 6.2% and 5.0% respectively.

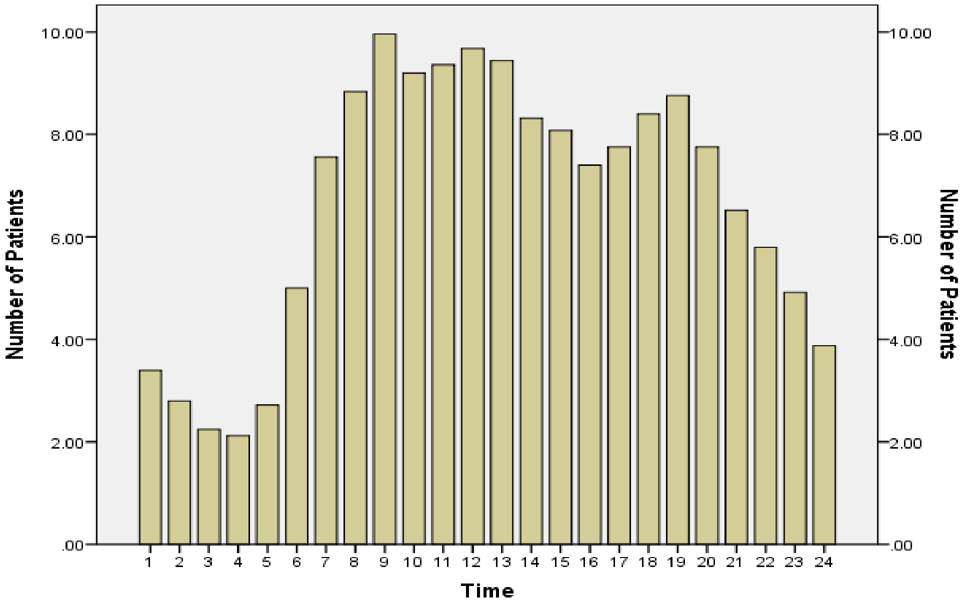

Figure 3-9. Patient arrival to the Emergency Department.

After being registered, patients wait for the availability of the triage room to be attended. In the triage room the acuity of each patient is checked based on the Manchester Triage System (MTS) that contains set of different flowcharts to help the caregivers in EDs to categorize patients into five priority groups including Immediate (Red), Very urgent (Orange), Urgency (Yellow), Standard (Green) and Non-urgent (Blue). Table 3-1 shows the level of priority for each category as well as the amount of time that each type of patient can stay in ED before being attended (Mackway-Jones, Marsden, & Windle, 2014).

Table 3-1. Safety minutes for patients until the first medical visit based on Manchester triage system.

Level of priority	Color	Safety minutes until first medical visit
Immediate	Red	Immediately
Very urgent	Orange	Up to 10 mins
Urgent	Yellow	Up to 60 mins
Standard	Green	Up to 120 mins
Non-urgent	Blue	Up to 240 mins

In order to categorize patients in different categories based on MTS and make the simulation able to improve the health condition of agents or worsen it, APACHE II (Acute Physiology and Chronic Health Evaluation II) is used. Originally an APACHE II is a severity of disease classification system in intensive care unit (ICU) that is calculated based on 12 routine physiological parameters (Knaus, Draper, Wagner, & Zimmerman, 1985). These parameters are as follow:

- AaDO2 or PaO2 (depending on FiO2)
- Temperature (rectal)
- Mean arterial pressure
- pH arterial
- Heart rate
- Respiratory rate
- Sodium (serum)
- Potassium (serum)
- Creatinine
- Hematocrit
- White blood cell count
- Glasgow Coma Scale

In this study, in order to generate agents with different acuities, we generated each factors randomly then, by using an online APACHE II score calculator the APACHE II for each agent is calculated in range of 0 to 30. Afterwards, the patients with higher score were categorized as patients with higher acuity. It should be noted that, the usage of APPACHE II score in this study is different from its application in calculating mortality rate in ICUs. Several studies including the study of Chiavone and Sens (2003) on the data from late 1990s from Santa Casa de Sao Paulo Hospital shows that higher APACHE II scores are correlated to high mortality rates in ICUs. In real world, the APACHE II score will be calculated only once when a patient enters ICU, but in our simulation, this number will be updated to in order to calculate death probability of agents.

After Triage room, the patients wait in waiting room for their number to go to one of the sections that can be seen in Figure 3-6 for their treatment. In each section, the doctor can send the patient to x-ray and laboratory for further exams. The treatment in each section needs some time to be done. In this dissertation, we studied two different cases, in order to avoid any confusion, the related data on each ED is given in the next chapter when the achieved results are explained.

3.5.1. Netlogo

Netlogo is an open source agent based simulation platform from Northwestern's Center for Connected Learning and Computer-based Modeling in Illinois, USA, (Wilensky & Evanston, 1999) and has been successfully applied in different fields of ABS. (Head, Hjorth, Brady, & Wilensky, 2015; Moore, Boone, Koyama, & Holfelder, 2014; Taboada et al., 2011). Numerous extensions of the Netlogo that connect this platform to other useful software such as MATLAB and EXCEL and user friendly interface, makes the Netlogo a proper simulation platform. Moreover, the capability of the Netlogo in providing 2D and 3D views of the model makes them easier to understand. Figure 3-10 shows the user interface of Netlogo 6.

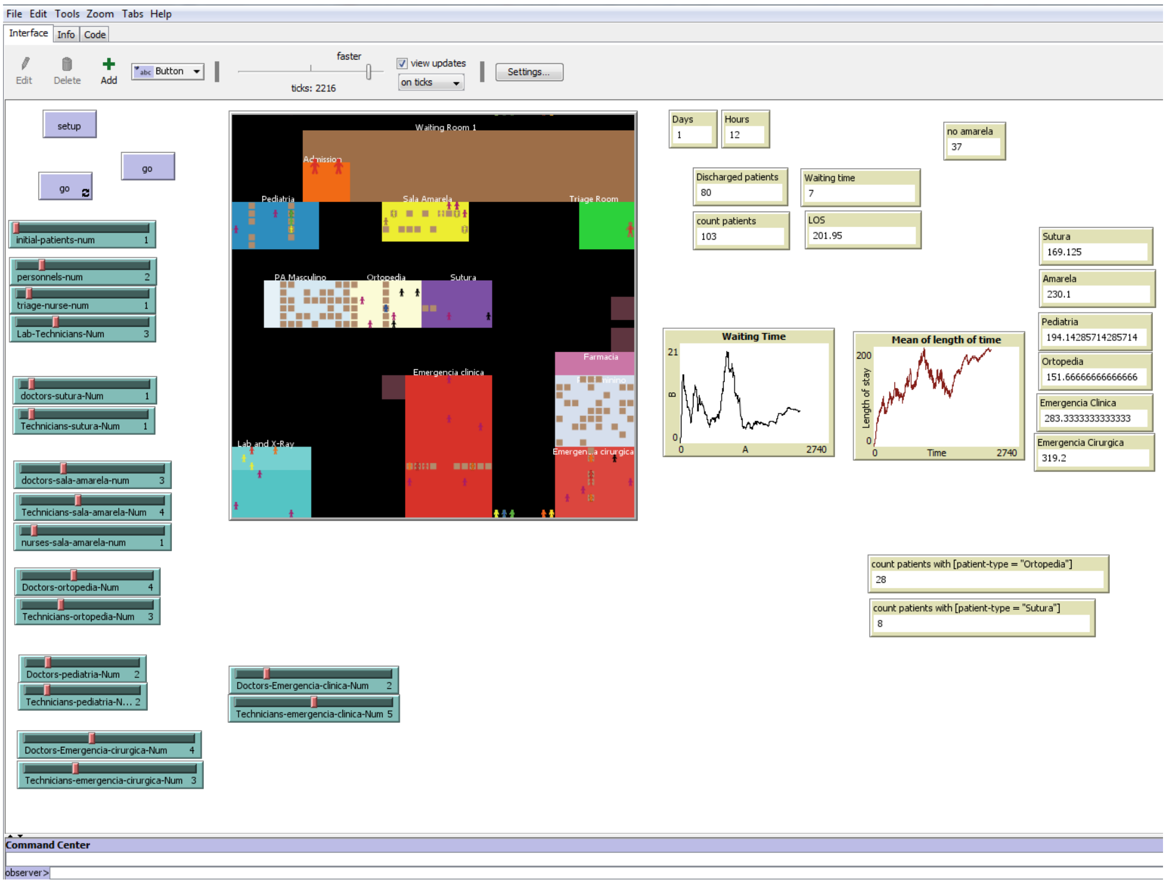

Figure 3-10. User interface of Netlogo 6.0.

One of the most useful tools of Netlogo is BehaviorSpace that is a software tool integrated with NetLogo that allows researcher to perform experiments with models. The process that sometimes calls “parameter sweeping” helps to explore the simulation space. For instance, suppose that a slider in Figure 3-10 can accept four numbers (1, 2, 3, 4) and the other one accepts three numbers (3, 4, 5) the BehaviorSpace can check all the possible solutions and run the simulation for the number of replications and provide the output in an Excel spreadsheet (Figure 3-11).

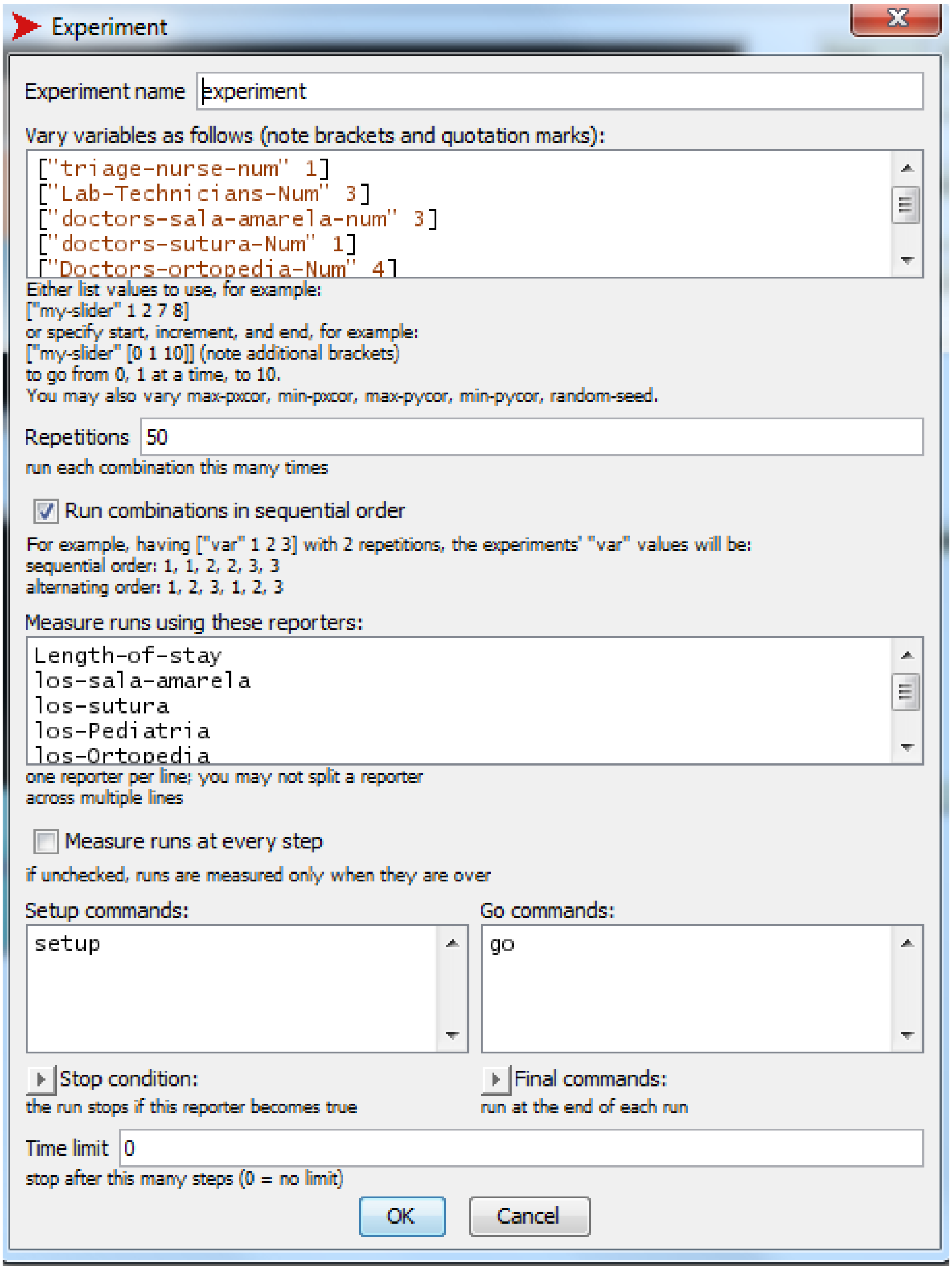

Figure 3-11. BehaviorSpace feature in Netlogo.

3.6. Design of experiments

The most accurate way to study the behavior of a simulation model and find the best configuration of resources may be to use complete enumeration. To do so, it would be necessary to perform a large number of experiments to cover all parts of the space in the domain of decision variables. Therefore, design of experiments (DOE) is used to find a sample that covers most space parts with the least number of simulation executions. In fact, DOE can be defined as a matrix, where columns represent factors (variables) and rows represent a sample (Cioppa, 2002).

There are different DOE and sampling methods, the most common being the 2^k factorial design where *k* is number of factors (Law, 2014). For instance, as our simulation has 19, if each variable has only two states, the number of experiments is $2^{19} = 524288$ Suppose we need 50 replications for each experiment and each run takes 60 seconds, we would need almost 50-year CPU time. When the number of factors increases, the model proposed by (McKay MD, 1979) and (Iman & Conover, 1980) is more efficient. Latin hypercube design (LHD) is a matrix with *m* rows and *k* columns, where *m* is the number of design points and *k* is number of variables. A rule of thumb for choosing the number of design points is $m = 10k$. Hence, in our case 10 x 19 = 190 experiments are needed. For more details regarding LHD see (Iman, 2008; Stein, 1987). In this study, lhsdesign Matlab extension is implemented to generate the samples[1].

Generally, more samples in metamodel training ensure better system performance but our network needs to be over-trained. To cope with this issue, LHD was employed in this study to create four different samples including 250, 500, 750 and 1000 experiments called M_1, M_2, M_3 and M_4 respectively. Subsequently, simulations of each of these design points were run to achieve the study objective.

3.7. The proposed Metamodel approach

The literature indicates that any artificial intelligence approach like ANN or ANFIS has its own advantages. Hence, each can outperform the others in a particular task, something that is well-

[1] Available at www.mathworks.com

documented for regression tasks in (Damousis & Dokopoulos, 2001; Taskaya-Temizel & Casey, 2005). Therefore in this study, an ensemble of different algorithms is applied to increase metamodel efficiency.

Three well-known machine learning algorithms were constructed and combined through two recognized methods, namely bagging and Adaboost, to determine the best possible metamodel for this task. A conventional feedforward neural network (FFNN), an adaptive neuro-fuzzy inference system (ANFIS) and a recurrent neural network (RNN) were tested. Overall, eight ensemble algorithms were constructed in this study. Figure 3-12 demonstrates a schematic of the process of creating a metamodel.

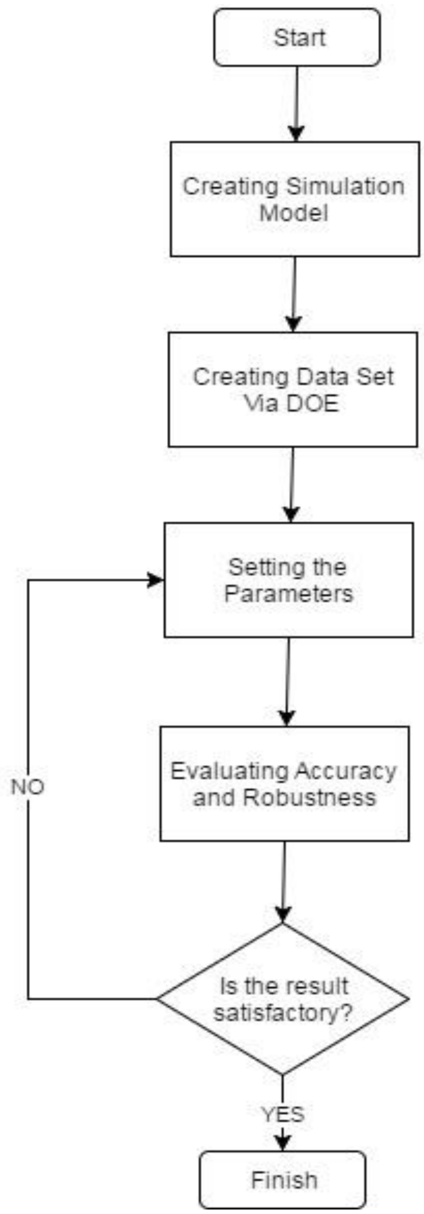

Figure 3-12. Process of creating a metamodel.

3.7.1. Feedforward neural network (FFNN)

A feedforward neural network contains three principal elements: input, output and hidden layers. Each constitutive unit (artificial neuron) is connected to other neurons in each layer. This connection is mathematically represented by the measure of the connection (weight) between two nodes in the network. In order to minimize the error function, these weights are changed in different steps of the learning process. The learning process eventually leads to the model being able to deal with any unknown sets of data. To select the weights in this artificial neural network (ANN), the Levenberg–Marquardt algorithm (LMA) is implemented. Figure 3-13 exhibits different parts of a simple feedforward neural network with one hidden layer.

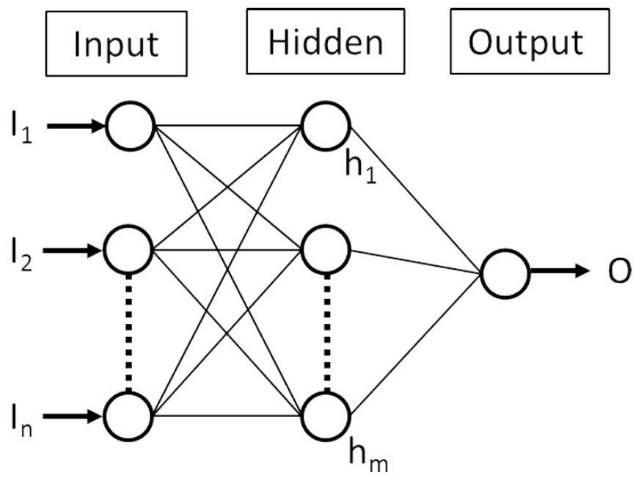

Figure 3-13. Diagram of a typical feedforward neural network with one hidden layer.

3.7.2. Layer-Recurrent neural network (RNN)

In a conventional ANN, it is assumed that all inputs are independent of each other and hence sequential information is not utilized. Recurrent neural networks (RNNs) are an extension of feedforward networks where each layer has a recurrent connection with a tap delay associated with it. This allows the network to have an infinite dynamic response to time series input data (Mikolov, Karafiát, Burget, Cernocký, & Khudanpur, 2010). The term “recurrent” refers to the ability of these networks to do the same task for every element of a sequence. To put it in perspective, RNNs are having a memory to capture and use the information about the previous calculations.

The LRNs are a variant of RNNs where a feedback loop with a single delay is utilized. All layers have this feedback loop except for the last layer. LRN is an enhancement of the network previously presented by Elman (1990).

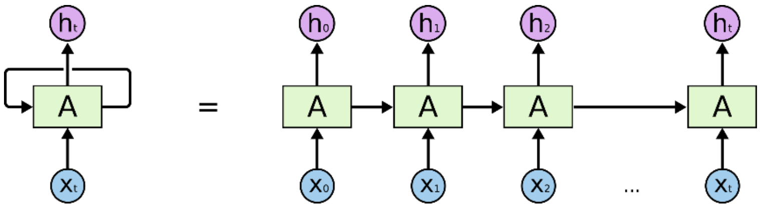

Figure 3-14. The chain-like nature of an unfold recurrent neural network.

In this study, backpropagation, similar to that of FFNN, is used for training the RRN.

3.7.3. Adaptive neuro-fuzzy inference system (ANFIS)

ANFIS architecture benefits from both fuzzy logic and artificial neural networks (Jang, 1993). The abilities of ANFIS have been proven in different areas of research, including time-series forecasting (Wang, Chau, Cheng, & Qiu, 2009), stock market forecasting (Boyacioglu & Avci, 2010; Kazem, Sharifi, Hussain, Saberi, & Hussain, 2013) and reducing the bullwhip effect in supply chains (Tozan & Vayvay, 2009; Yousefi, Yousefi, & Ferreira, 2015; Zarandi & Gamasaee, 2013). In ANFIS, a fuzzy inference system (FIS) is built and a backpropagation algorithm or a combination of a backpropagation algorithm with a least squares method is implemented to adjust the membership function parameters. This adjustment enables ANFIS to learn from the data available in the model.

Similar to neural networks, ANFIS is constructed from a network of input and output layers, where hidden layers connect the input and output layers. These layers are in fact membership functions and other related parameters.

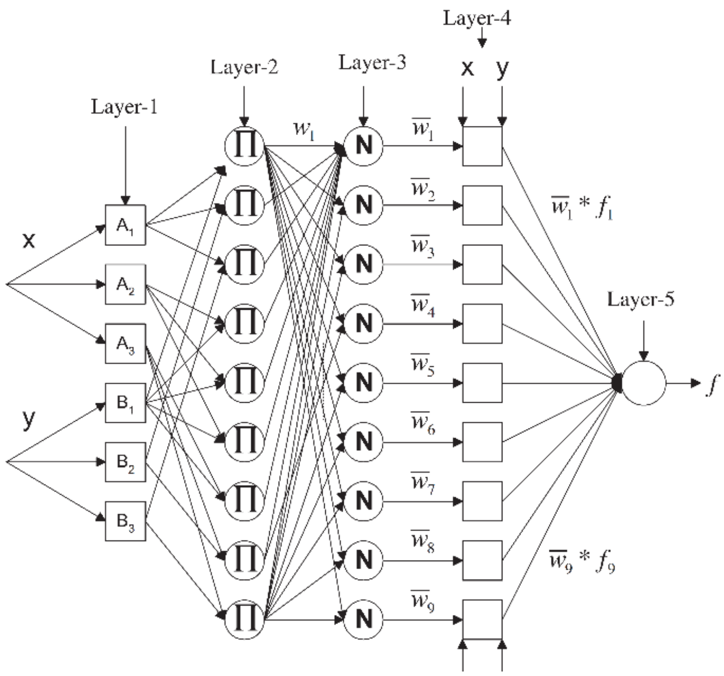

Figure 3-15. Flowchart of five-layer ANFIS with two inputs and one output.

As already mentioned, the process of adjusting the membership functions in ANFIS is the process that causes learning. A gradient vector is used to ease parameter calculation. This gradient vector for any given data set facilitates understanding how the fuzzy inference system maps the input and output data. Actually, it is necessary to apply an optimization method to minimize the error measure by adjusting the parameters once the gradient vector is created. This error measure can be defined as the mean squared difference between expected data and data from a real case. For membership function parameter estimation in ANFIS two approaches can be used: backpropagation or a combination of least squares estimation and backpropagation. Figure 3-15 demonstrates a simple five-layer ANFIS with nine if-then rules. This ANFIS has two inputs (x and y) and one output (f).

3.7.4. Ensemble approaches

There are generally two categories of ensemble approaches, namely competitive and cooperative algorithms. In the former, different predictors are used for the task, or the forecast is made based on different data sub-sets and a weighted average of the results is the final forecast. In the cooperative approaches, however, the forecasting task is divided into different sub-tasks where each sub-task is forecasted individually. The final result is the sum of all outputs (Dietterich, 2000). An example of a cooperative approach for times series forecasting is wavelet decomposition to pre-process the dataset and then employing a predictor to forecast the resultant data sets. The predicted data sets are then aggregated to achieve the forecast values (Ren, Suganthan, & Srikanth, 2015).

Among various competitive approaches, bootstrap aggregating (Bagging) and adaptive boosting (AdaBoost) have been shown to greatly affect the performance of machine learning approaches for both classification and regression tasks. Therefore, these two methods were selected to build a powerful ensemble metamodel.

3.7.5. Bootstrap aggregating (Bagging)

Conventionally abbreviated as Bagging, bootstrap aggregating basically entails training many models on separate training sets, hence providing data diversity, and then summing their results with the same weights to achieve a better model (Breiman, 1996; Sahu, Runger, & Apley, 2011). Bagging can prevent learning algorithm overfitting as random sampling is performed to train the initial algorithms. In this study, an N model is trained on N randomly drawn data sets with similar sizes. The N sub-data sets are drawn using the sampling with replacement method. Each individual metamodel is assigned a (1/N) weight and the bagging metamodel is built as follows:

$$F_T(x) = \left(\frac{1}{m}\right)\sum_{t=1}^{m} f_t(x) \qquad (8)$$

Where m is the number of approaches used in the ensemble method and F_T is the outcome of a given approach. Figure 3-16 demonstrates flowchart of the three-algorithm bagging ensemble approach.

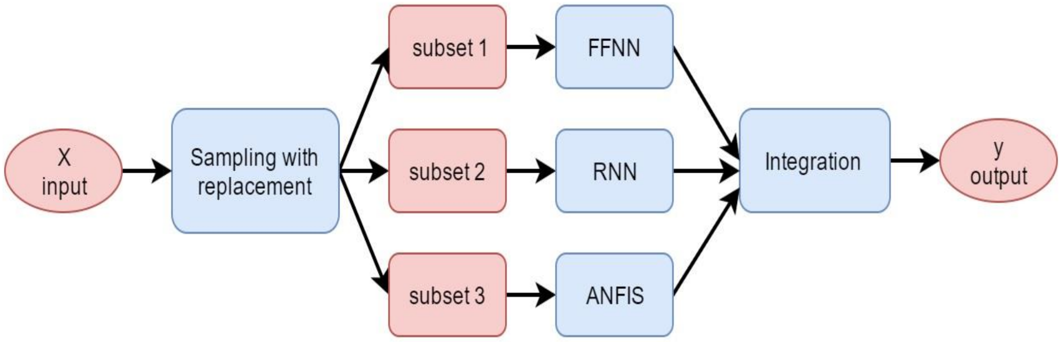

Figure 3-16. Flowchart of the three-algorithm bagging ensemble approach.

3.7.6. Adaptive boosting (AdaBoost)

AdaBoost is an adaptive ensemble approach specifically proposed for classification problems by Freund and Schapire (Freund, Schapire, & Abe, 1999). AdaBoost has mostly been used for classification problems, but recently, its successful application for regression and forecasting tasks has also been reported in literature (Liu, Tian, Li, & Zhang, 2015). Similar to bagging, a number of machine learning algorithms, which are called “weak learners,” are combined into a weighted sum to achieve better results than the weak learners. AdaBoost is different from bagging firstly because the sub algorithms do not have an equal weight in the final ensemble. Secondly, Adaboost is adaptive as it capitalizes on the samples with bigger errors and better-performing weak learners. Adaboost gives higher weightage to samples with poor training results and learners with good performance, and lower weightage to samples with good training results and learners with poor learning performance. Therefore, two sets of weights are to be adjusted in building an AdaBoost ensemble, namely the weights of the training samples and of the weak learners. The final predictor is built as follows:

$$F_T(x) = \sum_{t=1}^{m} \alpha_t f_t(x) \tag{9}$$

Where x is the input of the metamodel, F_T is the final ensemble, t is the number of weak learners, α_t is the weight of each weak learner and f_t is a weak learner.

In the beginning, the weak learners are trained on the same training set. Then the weighted ensemble is created by adding the weak learners to the ensemble one by one. The weight of all samples is assumed to be the same in the beginning and then based on this weight the samples are adjusted throughout the ensemble process.

Assuming $X=[x_1,....x_n]$ represents the training samples, $Y=[y_1,...y_n]$ is the desired output and $w=[w_{1,1},..., w_{n,1}]=1/n$ denotes the initial sample weights, the AdaBoost algorithm used in this study is summarized as follows.

When building an ensemble of m algorithms, in step $m-1$ the weighted sum of the algorithms is:

$$F_T(x_i) = \alpha_1 f_1(x_i) + \alpha_2 f_2(x_i) + \cdots + \alpha_{m-1} f_{m-1}(x_i) \tag{10}$$

Then for the m-th weak learner, the ensemble is extended to include the weak learner f_m such that by adjusting its corresponding weight, α_m, the total metamodel error is reduced. The AdaBoost computational steps are given as follows.

Step 1: Individually train the weak learners on the data set.

Step 2: Use the build learner f_t to predict the values of data set x_i and the associated modeling error for each sample as follows:

$$\xi_i = \frac{|y_i - \hat{y}_i|}{y_i} \tag{11}$$

$$\xi_m = \frac{1}{n}\sum_{i=1}^{n} \xi_i \tag{12}$$

Step 3: Calculate the weight of weak learner f_m:

$$\alpha_m = \frac{1}{2}\ln\left(\frac{1-\xi_m}{\xi_m}\right) \tag{13}$$

Step 4: Update the sample weights as follows:

$$w_m(i) = \frac{w_{m-1}(i)\beta_m^{-\xi_i}}{Z_m} \tag{14}$$

$$\beta_m = \frac{\xi_m}{1 - \xi_m} \tag{15}$$

Where Z_m is a normalizing factor so the sum of all weights throughout the sample becomes 1.

Step 5: Repeat steps 2-4 until all weak learners are added to the ensemble algorithm.

Four ensemble algorithms were tested in this study: FFNN-RNN (FR), FFNN-ANFIS (FA), RNN-ANFIS (RA) and FFNN-RNN-ANFIS (FRA). For each set of algorithms, the ensembles were created with both Bagging and AdaBoost, therefore a total of eight ensemble algorithms were tested to find the best metamodel for this problem.

3.8. Network performance evaluation

Metamodel performance was evaluated using two statistical indicators, namely mean absolute percentage error (MAPE) and coefficient of determination (R^2). MAPE is calculated as follows:

$$MAPE = \sum_{i=1}^{n} \left(\left| \frac{M_i - E_i}{M_i} \right| \times 100 \right) \Big/ n \tag{16}$$

Where n is the number of observations, E_i is the metamodel result, and M_i is the desired simulation result. MAPE provides information on metamodel performance, with lower values indicating better performance.

The coefficient of determination (R^2) is simply the square of the sample correlation coefficient between the metamodel outcome and the desired simulation result. This coefficient varies in the range of 0 to 1. The higher the value, the better the metamodel performance is.

3.9. Optimization approach

After creating the simulation model and making the metamodel, the next step is to apply an optimization approach to optimize the performance of ED subject to different constraints such as budget and capacity. Figure 3-17 illustrates the optimization approach proposed in this paper for using GA, but any other evolutionary approach can be replaced by GA to check the results.

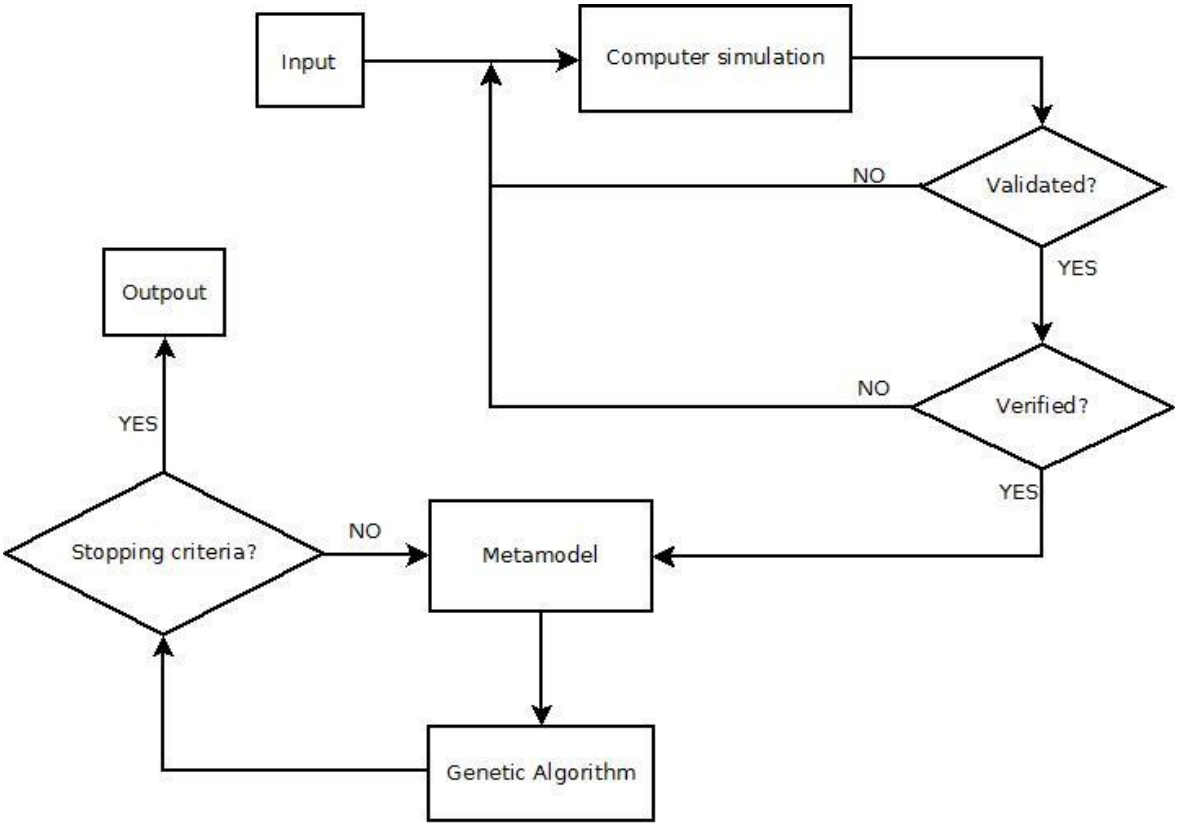

Figure 3-17. Combined optimization–simulation approach using the metamodel.

3.9.1. Genetic algorithm

Genetic algorithms (GAs) (Holland, 1975) mimic the process of natural selection, and similar to any other population-based algorithm, begin with generating a group of possible solutions. Each possible solution is called a chromosome in GA. The fittest chromosomes create the next generation with a crossover operator that makes them give part of their genes to the next generation, while a mutation operator helps keep the diversity of possible solutions high enough to avoid premature convergence.

Figure 3-18 shows the chromosomes used in this study. Each column, dubbed as a gene, consists of a number corresponding to a specific resource in the ED. Each chromosome must meet the pre-defined capacity and budget constraints. Any chromosome with a budget equal to or less than 68 cost units is feasible, provided that all its genes are in the prescribed range as described in Table 4-10. To evaluate the fitness of a chromosome a fitness function is used, which is replaced with a metamodel in this study.

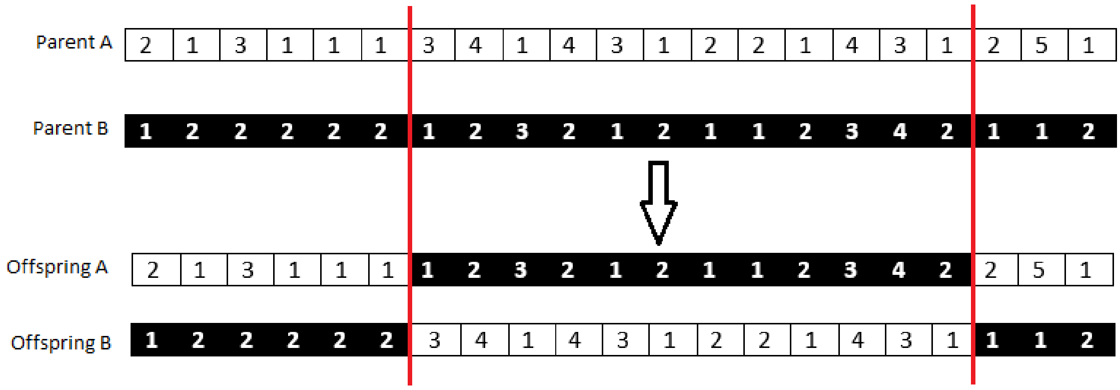

Figure 3-18. Genetic algorithm two-point crossover process.

To avoid trapping in local optima, a chaotic mutation operator is implemented in the GA similar to Coelho (2008). This mutation operator is easy to implement and computationally inexpensive. A one-dimensional logistic map is implemented for the mutation operator to generate a new solution. All elements of a chromosome are first scaled to the range of 0 to 1 and then a new chromosome is iteratively generated by using the classic logistic chaotic sequence as follows:

$$X_i^{(n+1)} = 4X_i^{(n)}\left(1 - X_i^{(n)}\right) \tag{17}$$

$$0 \leq X_i^{(n)} \leq 1 \tag{18}$$

$$X_0^{(n)} \neq 0, 0.25, 0.75 \textit{ and } 1 \tag{19}$$

Where n is the iteration number and k denotes the total number of chaotic variables. Having determined the new sequence, the variables are mapped to their respective real values.

Additionally, a penalty function is added to the fitness function to handle the constraints as GAs are generally unable to do so. A simple penalty function approach is implemented in this study. Selecting a high penalty parameter would eliminate the infeasible solutions from the search space, while a low penalty may result in infeasible final solutions. Therefore, the penalty parameters are set through an extensive trial and error process.

3.9.2. Imperialist Competitive Algorithm (ICA)

ICA is a population-based algorithm that mimics the human social evolution to solve optimization problems (Atashpaz-Gargari & Lucas, 2007). Like any other population-based approach, the algorithm begins with an initial population. Each individual in ICA terminology calls a country and the power of each country is calculated using the fitness function, the better result from fitness function, the more power for the individual (country). Although ICA same as particle swarm optimization (PSO) is continuous (Yousefi, Yousefi, Ferreira, & Darus, 2015; Yousefi, Yousefi, Hooshyar, & de Souza Oliveira, 2015), the discrete ICA has shown good performances in finding near optimum solutions in short computational times in different fields of studies (Yousefi et al., 2012; Yousefi & Yusuff, 2013).

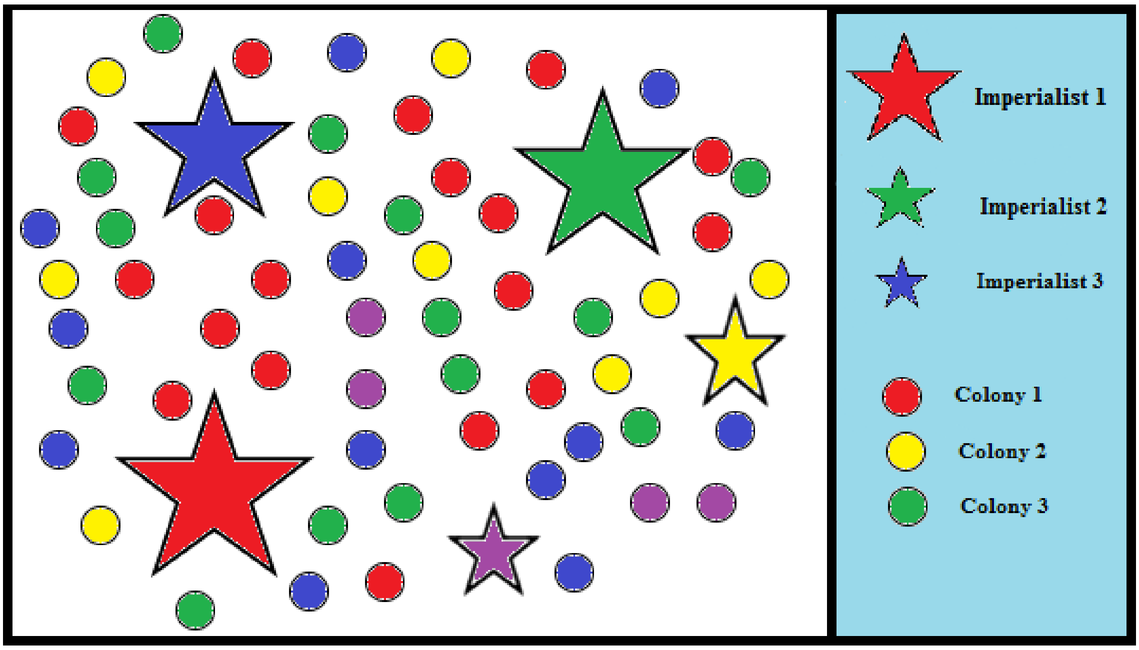

Figure 3-19. Creating initial population in Imperialist Competitive Algorithm.

The possible solutions (countries) in ICA are divided into two groups of countries based on their fitness function (power). Top-ranked countries are selected as imperialist countries, the weaker countries are colonies, and they will be divided among the imperialists to create empires (Figure 3-19). Each empire contains an imperialist country and some colonies. In each empire (group), the members are forced to change their characteristics (culture, language, etc. in real world) towards the imperialist to improve. This process of moving a colony towards an imperialist is called assimilation that will be replaced with a two-point cross over to adapt the ICA with discrete nature of the problem. Therefore, a two-point cross over between a colony and its imperialist make the colony to be more similar to its imperialist. The original algorithm could generally be described in six steps, which are as follows.

Step 1: Creating the initial population: This step is already explained. 100 countries are created in this step and we select top 10 of them as imperialist and the remain as colonies.

Step 2: Assimilation policy: That is the process of moving a colony towards its imperialist. (Figure 3-20)

Step 3: Revolution: This concept is inspired by GA when mutation keeps the diversity of the population high to scape local optima. The same sudden changes in some of the population in ICA is called revolution.

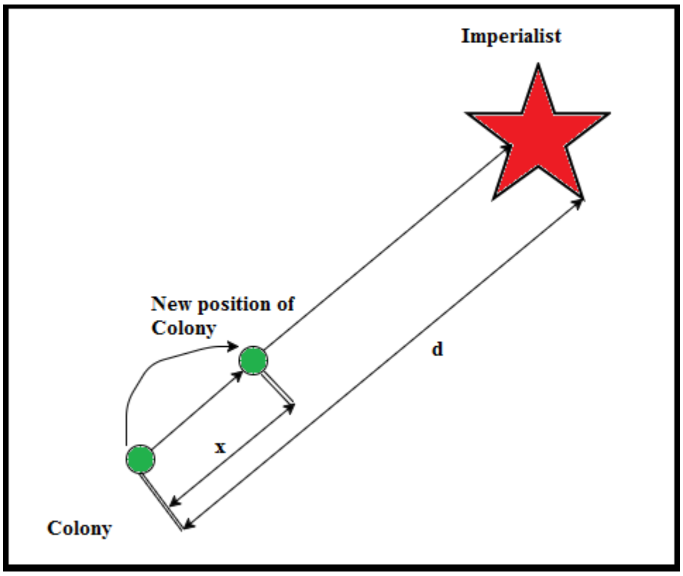

Figure 3-20. Process of assimilation in Imperialist Competitive Algorithm where a colony is forced to move toward its corresponding imperialist by x units.

Step 4: Updating the state of the empire: In any stage of the process if a colony reaches a better stage (stronger) than its own imperialist during a simulation policy, the position of colony and imperialist would change and the (more powerful) colony becomes the imperialist.

Step 5: Imperialistic competition: In each iteration of ICA, the imperialist participate in a competition with other empires to gain more colonies and subsequently be more powerful. We know that the total power of an empire is equal to power of the Imperialist plus power of its colonies. Therefore, possessing more colonies help the empire to be stronger. In this process, the weakest colony of the weakest empire is chosen and all empires have a chance of taking over of it based on their power. Eventually, the weakest empire loses all of its colonies and collapse.

Step 6: Convergence: The algorithm continues until only one empire remains. The last imperialist has best fitness function (the most powerful).

Chapter 4
Results and Discussion

4.1. Introduction

This chapter provides the results of this thesis, which are divided in two main parts. The first part presents the results from the extracted model from the literature, its results and the impact of the proposed group decision making on the performance of the emergency department. The second part of this chapter present the simulation results from our case study from Hospital Risoleta Tolentino Neves (HRTM), and then the performance of the proposed metamodel approach is presented. Afterwards, the optimization approach on resource planning in ED is discussed.

4.2. Simulation results

In this section, a simulation study from the relevant literature is chosen to implement an ABS in healthcare industry. Ahmed & Alkhamis (2009) implemented a discrete event simulation and it should be noted that their study has none of characteristics of agent-based simulations and the objective of this section is not comparing our results with them and only the data are extracted from this study. Figure 4-1 shows the flow of patients in this ED. In this case, patients will be treated in three different sections. The patients with non-urgent problems are discharged directly from triage room, patients with severe problems go to treatment room to be treated by a nurse and finally the patients with the more serious problems go to emergency room to be treated by a nurse and a doctor.

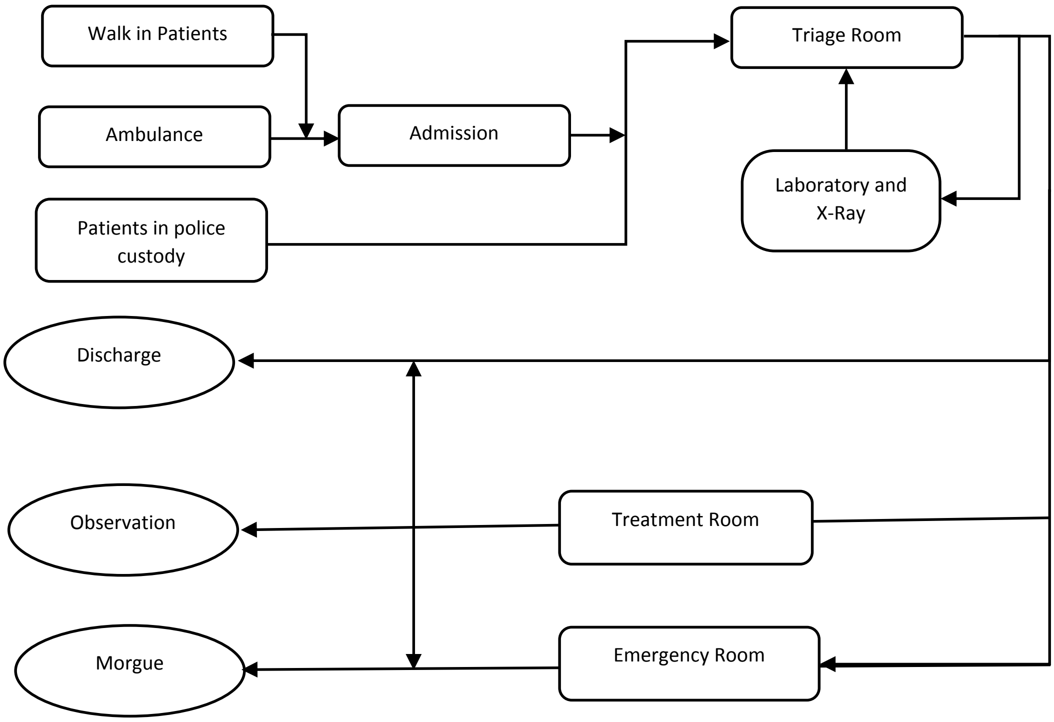

Figure 4-1. Patients flow in the emergency department.

The resources in this ED are limited to three receptionists, 12 emergency room nurses, six nurses (either for treatment room or triage room), five lab technicians and five doctors (either for triage room or emergency room). Each type of staff costs specific amount of budget to be used. In this case, a receptionist cost 0.4 budget units (BU), a doctor costs 1.2 BU, a Nurse and lab technicians costs 0.3 and 0.5 BU respectively. The total budget in this study cannot exceed 6.5 BU.

Figure 4-1 can be seen as a discrete event simulation than an agent based. After adding the behavioral parameters to the simulation the fellow of patients will be as in Figure 4-2. We assume that patients with high acuity do not leave the ED without being seen by a doctor, but other categorize have their own tolerance time and when they reach to that time they will decide to leave the ED. This decision is made based on the time they pass in ED and the experience of people around them.

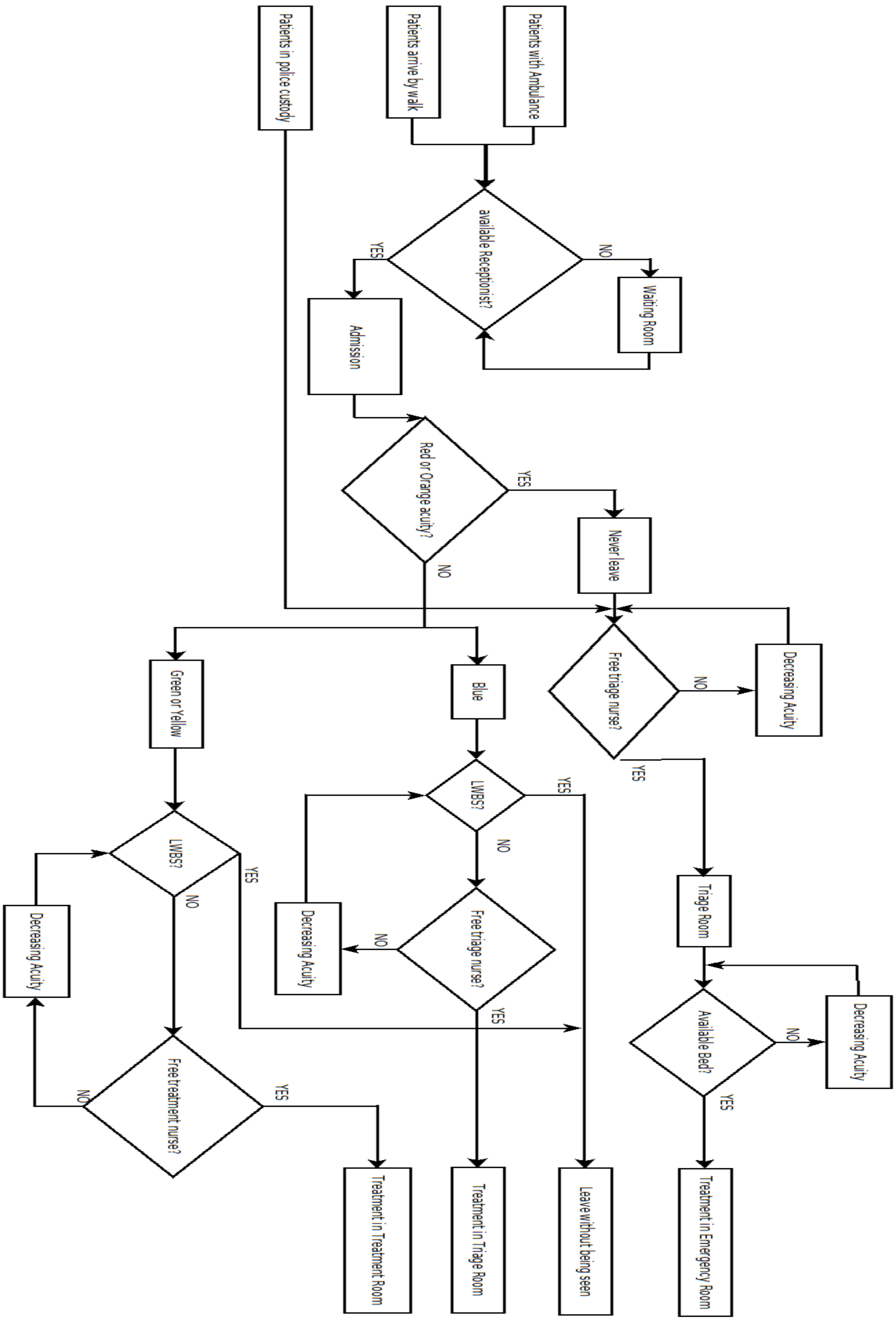

Figure 4-2. Patients fellow after considering LWBS.

In this study a novel approach of group decision making is proposed then the influence of applying this approach on key performance indicators (KPIs) is tested in different scenarios. The following paragraphs give a short presentation of each scenario and the KPIs will be introduced.

Table 4-1. Number of resources in each section of emergency department for six scenarios.

No	Number of receptionists	Number of ER doctors	Number of ER nurses	Number of Triage nurses / doctors	Triage error (%)	Number of TR nurses	Number of Lab technicians	Budget
1	1	2	2	3 nurses	33	4	2	6.5 BU
2	2	2	2	3 nurses	33	2	2	6.3 BU
3	2	3	2	2 nurses	33	1	1	6.4 BU
4	3	1	2	3 nurses	33	3	3	6.3 BU
5	2	1	1	2 doctors	0	2	2	6.3 BU
6	2	2	2	1 doctors	0	3	1	6.4 BU

ER: Emergency room
TR: Treatment Room

The focus of this scenario is on reducing waiting time in waiting room 2. Therefore, three triage nurses and four treatment room nurses are selected. While the scenario 4 is more focused on reducing the waiting time in waiting room 1 by applying three receptionists. It should be noted that in four of these scenarios nurses are in charge of working in triage room and in the rest doctors will do the triage task in triage room.

The process triaging process might be with some mistakes. For instance, almost one third of all assignments nurses in triage room are wrong and they categorize patients to a wrong category. Two concept of over-triage and under-triage are introduced to explain these types of mistakes (Van der Wulp, Van Baar, & Schrijvers, 2008). Under-triage is when a patient from orange category will be categorized as yellow. 25.3% of all errors are under-triage. 7.6% of errors are over-triage that happens when a patient should be in Orange category but the triage nurses put them in Red category. Error in triage might cause two scenarios. In the first one, the patient goes to a section to be treated, and then the staff discover that the patient has to go to another section. In the other case, the patient will leave the ED after receiving a non-proper treatment without discovering that. In this case, the patients are recognized as “wrongly discharged patients” that is one of KPIs in this study. Table 4-1 shows that the triage error when a doctor is working in triage room is equal to zero.

At the beginning of simulation, the ED is empty so the achieved results from that period is not reliable. As it can be seen in Figure 4-3 in this period, the average length of stay of patients have been fluctuated abnormally. This Figure shows that after almost 2880 minutes the behaviors of the simulation is back to normal. In this simulation, the model is run for three days (4320 ticks) but the data collection is limited to 2880 ticks to 4320 ticks that is 1440 ticks or a day in real world. It should be noted that in this simulation each tick is equal to one minute in real world.

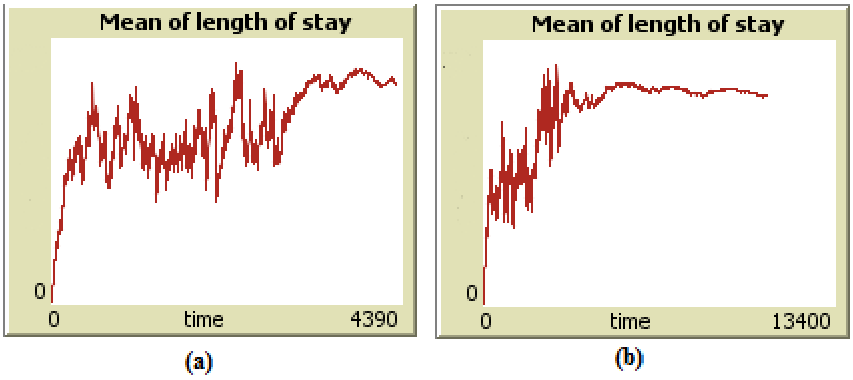

Figure 4-3. Warm-up period in simulation for 3 days (a) and for a week (b).

The simulation results show that all the characteristics of ABS are successfully added to this simulation. Table 4-2 shows the achieved results for all six scenarios with and without applying self-organization. Average waiting time is sum of waiting time in waiting room 1 and waiting room 2 for those who are discharged from ED. For each scenario, the simulation ran 200 times: 100 times without self-organizing and 100 times with self-organizing.

Table 4-2. Comparison of different scenarios with/without applying self-organizing.

No	Self-organization	Mean of TWT	Mean of LOS	LWBS	Number of deaths	Wrongly charged	Total output
1	N	126	269.4	10.38	0.90	10.58	134.59
	Y	95.5	228	7.36	0.80	10.64	153.41
2	N	84	211.2	4.97	0.86	14.83	170.41
	Y	74.4	204.6	4.32	0.80	14.92	184.05
3	N	151.2	299.4	10.04	0.95	10.75	114.84
	Y	136.8	279.6	8.42	0.85	13.30	133.47
4	N	79.8	208.8	4.40	0.90	14.72	167.42
	Y	68.4	190.8	3.84	0.84	14.78	181.28
5	N	146.4	290.4	8.95	0.91	0	130.02
	Y	124.8	274.2	8.03	0.83	0	147.01
6	N	290.4	427.2	12.04	1.46	0	70.31
	Y	284.4	419.4	11.39	1.34	0	77.26

LOS: Length of stay

TWT: Total waiting time
LWBS: Leave without being seen

It should be noted that in self-organizing process, no new resources will be added to the model. The number of staff agents and type of them will be fixed but they can go to other sections and work there. Figure 4-4 shows that scenario 1 has the highest change rate with applying self-organizing and its ALOS and total waiting time are reduced by 15.3% and 24.25 respectively, while the total reduction in all cases for LOS is 6.8% and for waiting time is 12.7%.

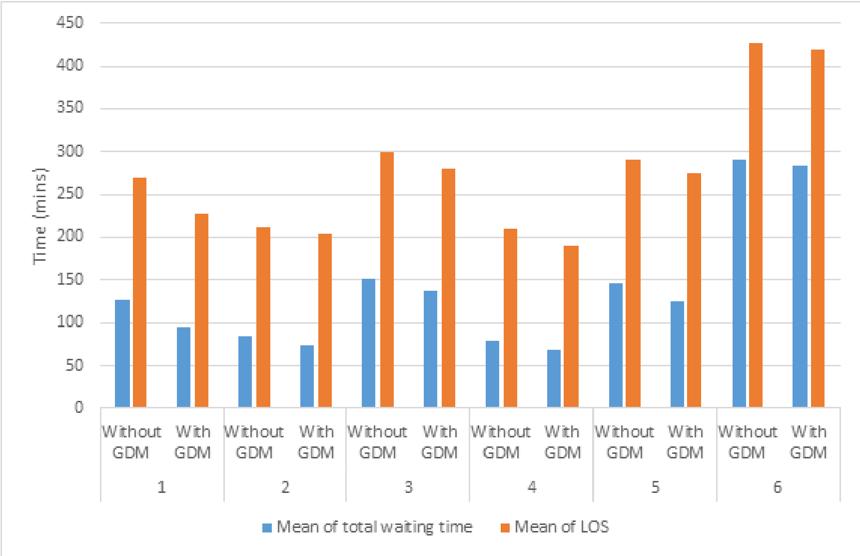

Figure 4-4. Comparing the results with/without self-organizing.

Figure 4-5 demonstrates the results for all six scenarios on three KPIs including LWBS, wrongly discharged and total output of the ED. The number of deaths are neglected from these analyses because the differences in each scenario is not a big number.

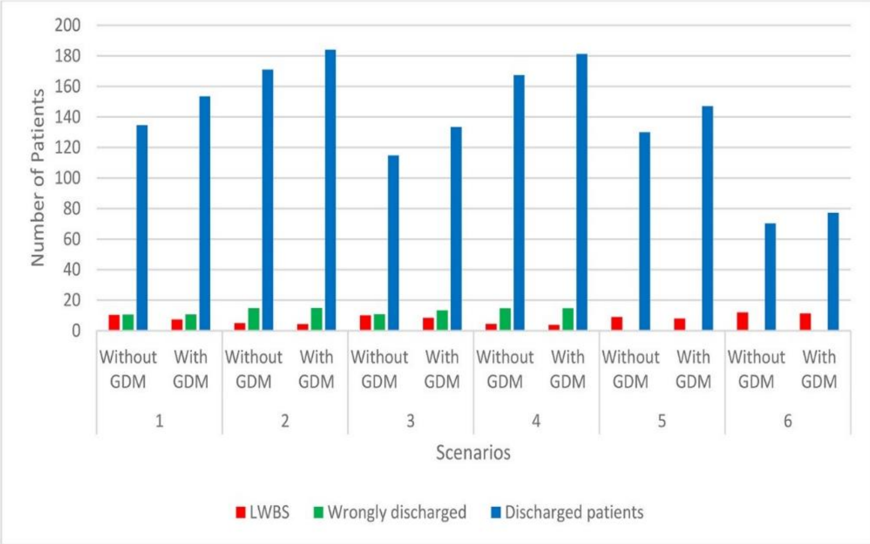

Figure 4-5. Comparison of LWBS, Wrongly discharged and discharged patients.

4.3. Risoleta Tolentino Neves Emergency Department

4.3.1. System description

Hospital Risoleta Tolentino Neves (HRTN) is a teaching hospital in the capital of Minas Gerais state of Brazil, Belo Horizonte. The HRTN emergency department operates 24/7 and receives 162 patients a day on average. HRTN as a part of public health network of the country is responsible to provide service for the patients of clinical and surgical urgency, traumatology and non-traumatology to cover a population of about 1.1 million people in the north of the metropolitan region of Belo Horizonte. The ED contains different sections: pediatrics, orthopedics, suturing, yellow zone and emergency rooms (surgical and clinical). Each of these sections provides services for patients based on their problems. The yellow zone and clinical emergency respectively received the most and least patients among all sections, with 44% and 5% of all patients in the first half of 2016. The main resources in this ED are as follows:

1. Receptionists
2. Triage nurses
3. Doctors
4. Nurses
5. Nurse technicians

At one time, two receptionists, one triage nurse, 22 doctors, five nurses and 29 nurse technicians are working in the ED. Figure 4-6 demonstrates the flow of patients in the ED. The procedure starts with patient arrival to the department. Patients may arrive by themselves, by ambulance, or in police custody. All patients except for those in police custody must visit a receptionist to register their personal information. Subsequently, they go to a triage nurse in the triage room. In the triage room, the patient's acuity is checked based on the MTS.

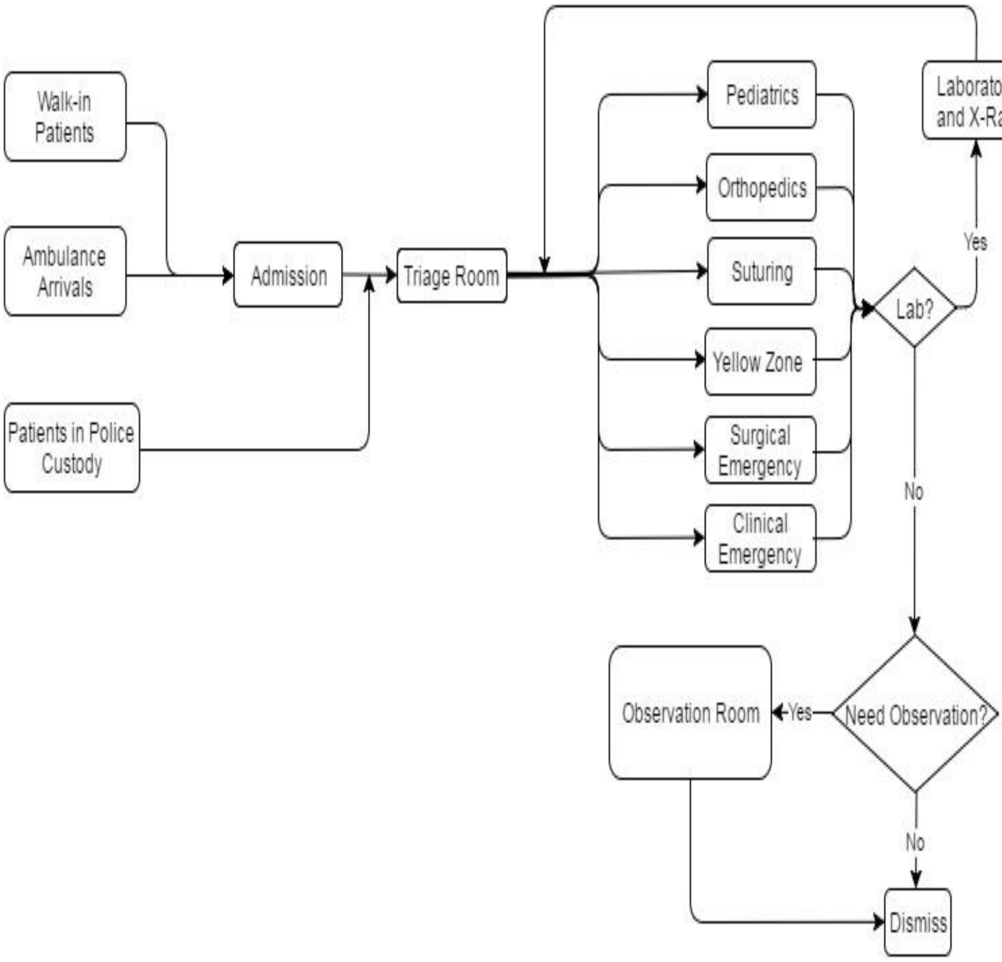

Figure 4-6. Flow of patients at the emergency department of the Risoleta Tolentino Neves Hospital.

Following triage, patients wait for the availability of the section where they need to be treated. Except for the suturing section, all sections contain beds. Patients in any section might go to the laboratory or X-Ray section for further examination and later return to their relevant section. After treatment in each section, the patient may leave the department or, depending on necessity, they go to the observation room. The process in the ED begins with registration for admission and concludes when the patient is released.

4.3.2. Simulation model

To simulate the mentioned system, the same simulation structure from last section is used. In order to make a reliable ED simulation model, data collection is needed. The main data collection elements in this simulation are as follows: the amount of time each service takes (admission, triage, laboratory, etc.), patient arrival rate and the number of each type of patients in the ED. From January 2016 to May 2016 around 24000 data were collected and analyzed to achieve proper model inputs. One-fourth of the gathered data were used for model validation and 75% served as input to create the model. The patient arrival to the ED is a non-homogenous Poisson process with a rate $\lambda(t)$ and 24 intervals as demonstrated in Figure 4-7, where $\lambda(t)$ is the estimated function of patient arrival per hour. Data analysis showed that 44% of patients go to the yellow zone, 30% go to the orthopedics section, 7.8% go to pediatrics and 7.0% go to surgical emergency, while the suturing section and clinical emergency rates are 6.2% and 5.0% respectively.

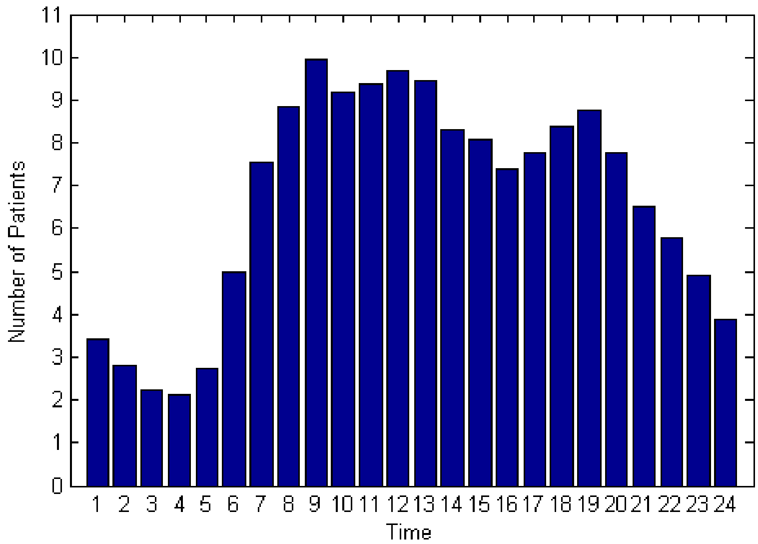

Figure 4-7. Patient arrival to the emergency department in RNTH.

The following tables provide some information about the time that patients might spend in each section of emergency department. Table 4-3 shows the length of service/treatment in each section, which is estimated by distribution. Table 4-4 demonstrates the needed time to prepare a bed to receive a new patient in each section. Table 4-5 shows that the amount of time that each patient will spend in a section after the treatment to leave the section and make the bed available for cleaning and receiving new people. Since the data collection for each action in each section need much effort, some of the data were estimated after consulting with some healthcare staff and some experts in simulation. This study tries to add more details to its agent to make the simulation as close as possible to the reality. To avoid any confusion in this part, more detailed data about agents i.e. amount of time to walk from one section to another one and energy level of healthcare givers are provided in appendix.

Table 4-3. Service/treatment time in each emergency department section.

No	Section	Distribution (min)
1	Admission	Uniform (3, 6)
2	Triage Room	Uniform (3, 5)
3	Suturing	Triangular (15, 20, 40)
4	Yellow zone	Triangular (10, 20, 25)
5	Orthopedics	Triangular (5, 10, 15)
6	Pediatrics	Triangular (10, 15, 30)
7	Surgical emergency	Triangular (10, 15, 30)
8	Clinical emergency	Triangular (10, 20, 30)
9	Lab and X-Ray	Triangular (15, 30, 45)

Table 4-4. Needed time to be prepared for a new patient.

No	Section	Distribution (min)
3	Suturing	Uniform (2, 5)
4	Yellow zone	Uniform (10, 15)
5	Orthopedics	Uniform (5, 10)
6	Pediatrics	Triangular (10, 15, 30)
7	Surgical emergency	Triangular (35, 50, 60)
8	Clinical emergency	Uniform (15, 30)
9	Lab and X-Ray	Triangular (5, 7, 12)

Table 4-5. Recovery time for each section in emergency department.

No	Section	Distribution (min)
3	Suturing	Uniform (3, 5)
4	Yellow zone	Uniform (10, 15)
5	Orthopedics	Uniform (10, 15)
6	Pediatrics	Uniform (10, 20)
7	Surgical emergency	Uniform (20, 30)
8	Clinical emergency	Uniform (20, 30)

4.3.3. Warm-up and number of replications

At the beginning of simulation, the ED is empty therefore the fluctuation in ALOS is too high and the results from this period is not reliable. To eliminate any bias at the beginning of the simulation, the model was run for 4320 minutes (3 days). The first 2880 minutes (2 days) were set as the warm-up period to make the simulation reach steady state and the remaining time was selected as the study period to collect the results. Figure 4-8 shows that the fluctuation of mean length of stay decreases after 2880 minutes of simulation time.

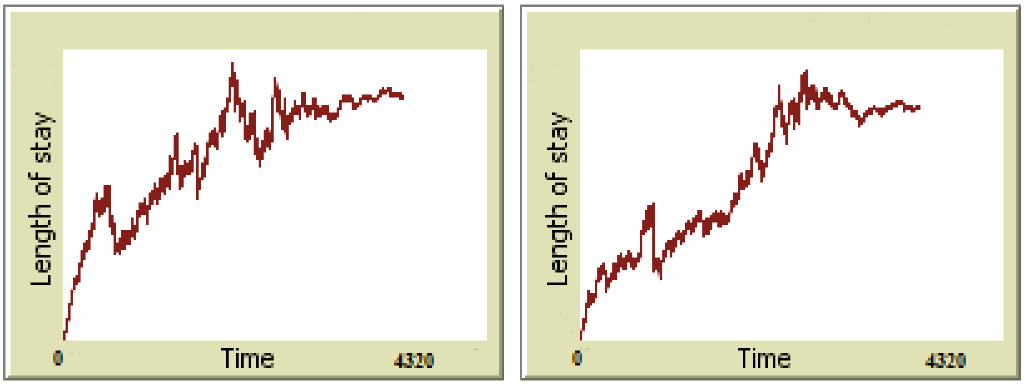

Figure 4-8. Warm-up period in simulation.

In simulation of a dynamic system like our problem, it is practically impossible to have the same results from different runs. To solve this issue, we need to have various replications of the simulation to use mean of all of them as an answer. To select the number of replications we made an independent samples t-test. An independent samples t-test has a null hypothesis (H_o) and alternative hypothesis (H_1) of the independent samples T test can be explained in two different but similar ways:

H_o: $\mu_1 = \mu_2$ (“the two population means are equal”)
H_1: $\mu_1 \neq \mu_2$ (“the two population means are not equal”)
OR
H_o: $\mu_1 - \mu_2 = 0$ (“the difference between the two population means is equal to 0”)
H_1: $\mu_1 - \mu_2 \neq 0$ (“the difference between the two population means is not 0”)

Where μ_1 is the mean of group 1 and μ_2 stands for the mean of group 2.
When we prove that there is no significance difference between two set of data we can use their mean interchangeably. For instance, the mean of 5 replications of a simulation can be compared with the mean of the other group of 5 replications. To avoid having too much computational time the less replications number is more suitable.

The confidence interval to compare the simulation results with actual results was set at 95% (a = 0.05). For all performance metrics, the error margin of each confidence interval was calculated by trial and error. To approximate the number of replications, this process continued until the margin of error was less than 5% of the average mean while the simulation computation time was tractable.

4.3.4. Verification and validation

Verification and validation are two of the most significant steps in any model simulation. Verification entails verifying whether the simulation model works as it should. In fact, verification deals with creating the model correctly. In comparing the animation created in our simulation with the ED routine, the district coordinator of hospital services verified the current version of the simulation model and confirmed that the output of this simulation can represent a real case study.

Validation concerns building the right model. Therefore, by calibrating the model, comparing its behavior with actual system behavior and repeating this process, the simulation model can be improved until it is acceptable. In this process, a set of data that was not used to create the simulation was used to prove that the simulation model is an accurate representation of a real case study. To validate the simulation model, the total time that patients spent in the ED was extracted from the Emergency Department Information System (EDIS) and compared with the total length of stay from the simulation (Table 4-6). The comparison validates there were no significant differences between the results obtained using the simulation model for the length of stay of patients in different ED sections and those from the real system (95% confidence level, a = 0.05). Moreover, the simulation throughput for a week was 1112 while the throughput for the real system was 1120. This also shows that the simulation was validated.

Table 4-6. Comparison of length of stay from simulation and the emergency department information system.

No	Section	Actual time	Simulation time	Confidence interval (95%)
1	Suturing	196.45	202.4	[180.35- 212.25]
2	Yellow zone	412.46	401.3	[361.10-429.92]
3	Orthopedics	180.45	192.6	[177.32-199.47]
4	Pediatrics	310.72	318.8	[286.65-342.54]
5	Surgical emergency	438.76	442.6	[401.21-471.52]
6	Clinical emergency	487.41	498.1	[462.12 – 513.68]

4.3.5. Resource allocation problem

As mentioned previously, ED resources are extremely restricted. Therefore, the aim of this study is to aid ED managers to allocate their resources in the best way so as to minimize ALOS subject to the problem constraints, which are capacity and budget. The problem can be written as follows:

$$Min\ Z = f\ (X_1, X_2, \dots, X_n), \tag{1}$$

S.t

$$\sum_{j=1}^{i} C_i X_i \ \le B\ , \tag{2}$$

$$l_j \ \le\ X_j \ \le\ u_j \quad for \qquad j = 1, 2, \dots, 5, \tag{3}$$

$$X_j\ integer \qquad for \qquad j = 1, 2, \dots, 5. \tag{4}$$

In Eq. (1), Z stands for the total ALOS in the ED and $(X_1, X_2, \dots, X_n)$ are decision variables. In fact, Z has no analytical form and it is the output of the simulation model mentioned in previous sections when the decision variables change. The cost of each resource and the budget are denoted by C_i and B respectively. It should be noted that due to ethical issues, we are not mentioning any salary from the real case. Instead of that, a series of salaries in the same area are extracted from resources then we transformed them to cost units[2] .

Table 4-7 illustrates that the capacity levels have an upper bound (u_i) and lower bound (l_i), which are the maximum and minimum capacity levels with a baseline value for the resources in the current ED situation. It should be noted that the same nurses cover three sections, including the yellow zone, orthopedics and pediatrics.

Table 4-7. Capacity levels and relative cost of resources in each section.

Section	Resources	Upper bound	Baseline value	Lower bound	Cost (CU)
Reception	Receptionist (x_1)	3	2	1	0.45
Triage Room	Triage Nurse (x_2)	3	1	1	0.75
Lab and X-Ray	Laboratory Technicians (x_3)	3	3	1	0.6
Suturing	Doctors (x_4)	3	1	1	2.9
	Nurse Technicians (x_5)	3	1	1	0.75
	Nurses (x_6)	1	1	1	1.1
Yellow zone	Doctors (x_7)	5	3	1	2.9
	Nurse Technicians (x_8)	6	4	1	0.75
	Nurses (x_9)	1	1	1	1.1
Orthopedics	Doctors (x_{10})	6	4	1	2.9
	Nurse Technicians (x_{11})	5	3	1	0.75
	Nurses (x_{12})	1	0	1	1.1
Pediatrics	Doctors (x_{13})	4	2	1	2.9
	Nurses Technicians (x_{14})	4	2	1	0.75
	Nurses (x_{15})	1	0	1	1.1
Surgical emergency	Doctors (x_{16})	6	4	1	2.9
	Nurse Technicians (x_{17})	5	3	1	0.75
	Nurses (x_{18})	2	1	1	1.1
Clinical emergency	Doctors (x_{19})	4	2	1	2.9
	Nurse Technicians (x_{20})	7	5	1	0.75
	Nurses (x_{21})	2	1	1	1.1

CU: Cost Unit

[2] www.guiadacarreira.com.br

4.4. Simulation's Results

Figure 4-9 shows the user interface of the simulation that has a graphical view for the users. Netlogo has three main parts including interface, info and code. The last one as it comes from its name is for writing the code to make the simulation. The info part optionally used to give some information about the model and the simulation. The interface section is what the last user is dealing with. In this section, the user is able to control the variables and see the animation from the simulation. Moreover, this section makes the user able to see some of the important results in real time.

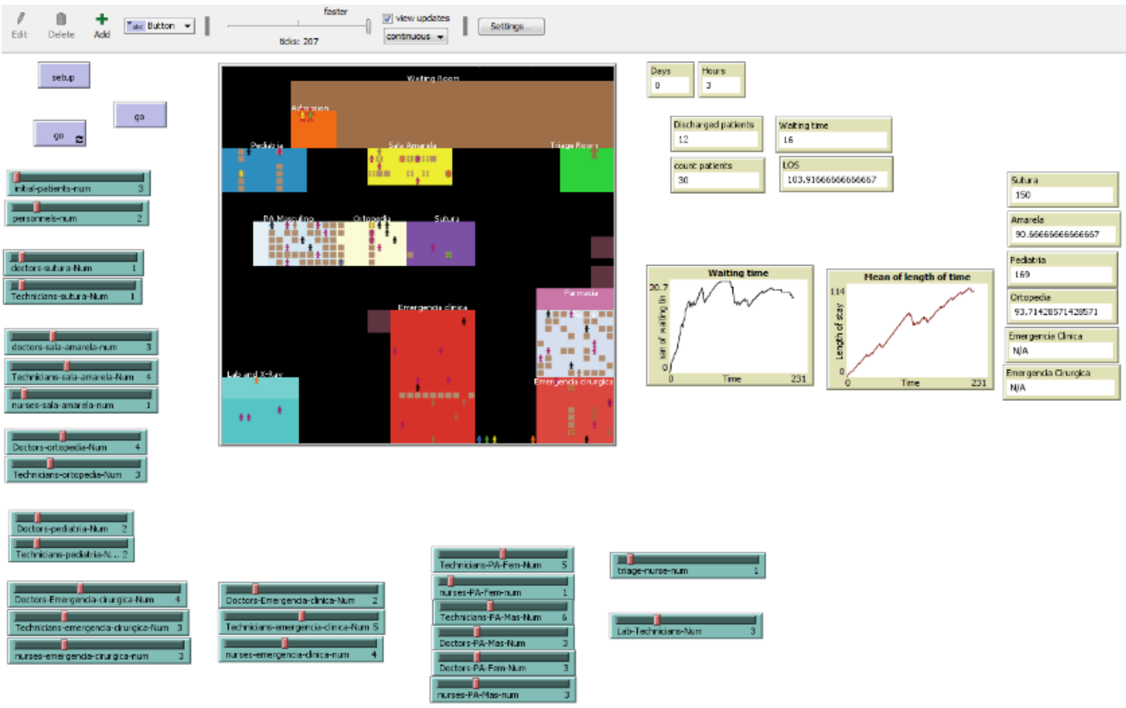

Figure 4-9. The user interface of simulation platform.

Studying the system behavior signifies that the yellow zone section has the most effect on ALOS because not only did it receive the majority of patients but the treatment in the yellow zone was also time consuming. As illustrated in Table 4-9, the yellow zone resources increased more than other sections. Figure 4-10 shows the impact of changing the number of doctors and nurse technicians in the yellow zone while other resources remain the same. It should be noted that some of these resource allocations are not feasible and they do not meet the budget constraints.

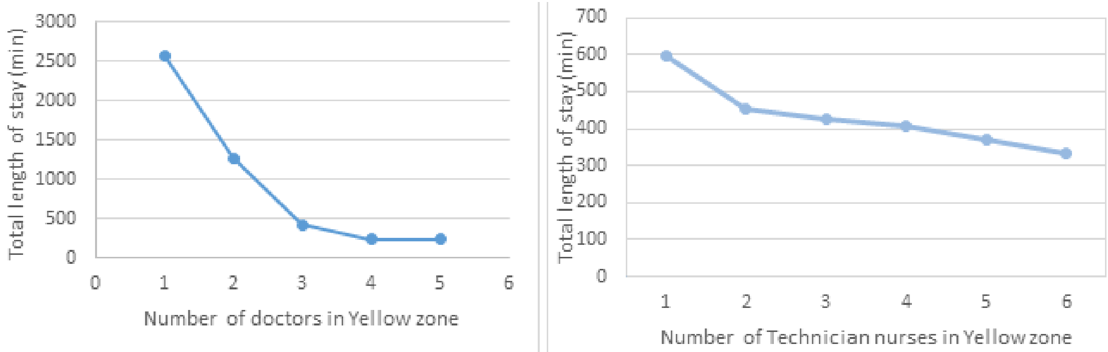

Figure 4-10. Impact of changing the number of doctors and technician nurses in the yellow zone on the total length of stay.

Another important factor in improving emergency department performance is the number of triage nurses (Figure 4-11).

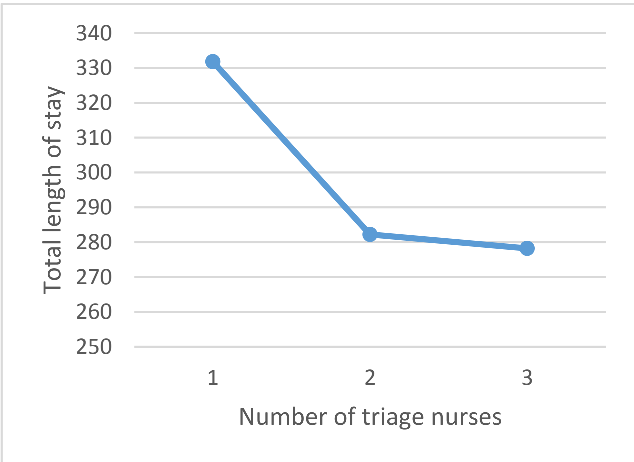

Figure 4-11. Impact of changing the number of triage nurses on the average length of stay.

4.5. Computational Results

4.5.1. Data set size

Before creating the ensemble algorithms, the size of the data set to be used for the metamodel should be selected. A low number of training data could result in low metamodel accuracy, while an excessive number of samples may yield overfitting. Moreover, computation time increases with sampling size. A primary metamodel was created with four training sample sizes, namely M_1=250, M_2=500, M_3=750 and M_4=1000.

For all cases, the test data set size was 200 and the samples were independent of those used for training.

4.5.2. FFNN

A three-layer feedforward neural network consisting of one input, one output and one hidden layer was utilized in this study. The input is a set of vectors that represent the decision variables of the simulation model and the output layer is a single point representing the simulation output. The activation functions used for the hidden and output layers are the hyperbolic tangent (tansig) and linear (pure-lin) functions, respectively. Three training algorithms, i.e. Levenberg-Marquardt (LM), Resilient Backpropagation (RB) and Scaled Conjugate Gradient (SCG) were initially tested and owing to the better performance of the LM algorithm, it was chosen for the metamodel. The number of neurons in the hidden layer was selected by trial and error, as is the case in literature. Through extensive experimentation, the optimum neural structures were found to be 5, 7, 8 and 10 for cases M_1, M_2, M_3 and M_4 respectively. Figure 4-12 shows the structure of FFNN, in MATLAB, which is used to build the metamodel.

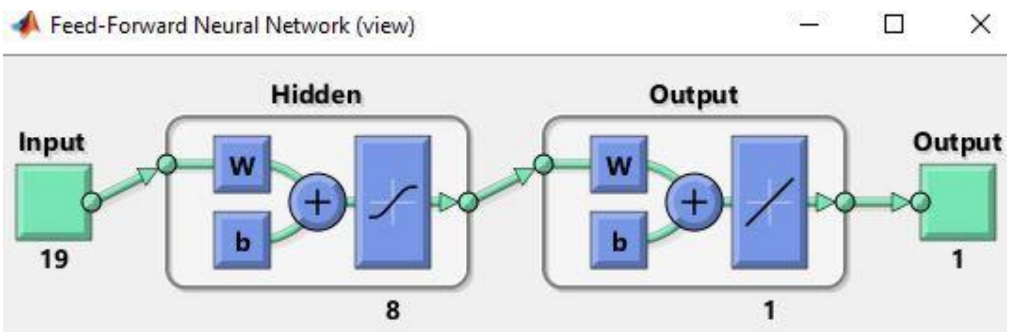

Figure 4-12. Feed-Forward Neural Network.

Table 4-8. The Computational time for each Metamodel approaches.

		M_1	M_2	M_3	M_4
FFNN	Training	0.250950 s	0.299176 s	0.328558 s	0.424925 s
	Test	0.007595 s	0.007793 s	0.008646 s	0.008638 s
RNN	Training	0.304357 s	0.457296 s	0.514948 s	0.751228 s
	Test	0.009160 s	0.009238 s	0.009271 s	0.009362 s
ANFIS	Training	1.452310 s	1.653425 s	1.864532 s	2.001325 s
	Test	0.014321 s	0.014651 s	0.015732 s	0.034512 s

4.5.3. RNN

Similar to FFNN, Levenberg-Marquardt served as the training algorithm and the network structure was found through trial and error. The RNN network was created in MATLAB with an available customized function. The input and output data set is similar to that of FFNN (similar size) and the optimum number of neurons were found to be 5, 7, 8 and 10 for cases M_1, M_2, M_3 and M_4 respectively. Figure 4-13 shows the structure of RNN, in 'MATLAB' used to build the metamodel.

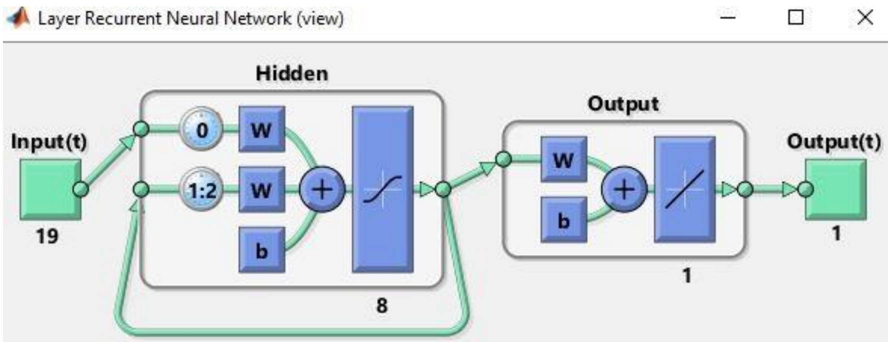

Figure 4-13. Layer Recurrent Neural Network.

4.5.4. ANFIS

To develop an ANFIS for the metamodel task, which is similar to a prediction problem, the same approach as in (Jovanović, Sretenović, & Živković, 2015) was employed. An initial fuzzy model was required to find the number of inputs, number of linguistic variables and consequently, the number of fuzzy rules in the final model.

The subtractive clustering method proposed by Chiu (1994) was applied to the input–output data pairs to extract the initial fuzzy model. It is a fast unsupervised method for estimating the number of clusters and their cluster centers by measuring the potential of data points in the feature space. Having estimated the clusters, the number of fuzzy rules and the premise fuzzy membership functions should be determined. For models M_1, M_2, M_3 and M_4, a Gaussian membership function with 4, 5 and 9 and 12 fuzzy rules, respectively, was considered. The number of fuzzy rules was attained through an optimization procedure using the least squares method and a hybrid learning algorithm.

Table 4-9. Performance of FFNN, RNN and ANFIS with different training data sets

Training	R^2				MAPE (%)			
	M_1	M_2	M_3	M_4	M_1	M_2	M_3	M_4
FFNN	0.9836	0.9839	0.9889	**0.9907**	3.6416	3.4402	3.4378	**3.227**
RNN	0.9764	0.9771	0.9785	**0.9903**	4.3241	4.1287	4.0952	**3.4791**
ANFIS	0.9771	0.9825	0.9892	**0.9895**	3.5712	3.3601	3.3319	**3.3041**
Test								
FFNN	0.9752	0.9816	**0.9852**	0.9641	3.8924	3.6601	**3.6584**	4.2422
RNN	0.9690	0.9710	**0.9787**	0.96004	4.9567	4.3475	**4.1002**	4.3674
ANFIS	0.9753	0.9812	0.9875	**0.9883**	3.8736	3.5733	3.5005	**3.5891**

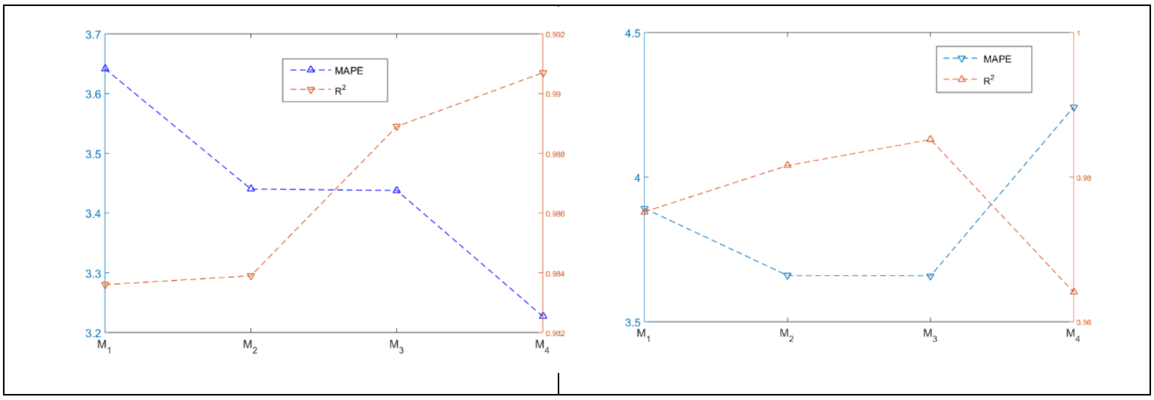

Figure 4-14.The performance of FFNN on different data sets: (a) training (b) test.

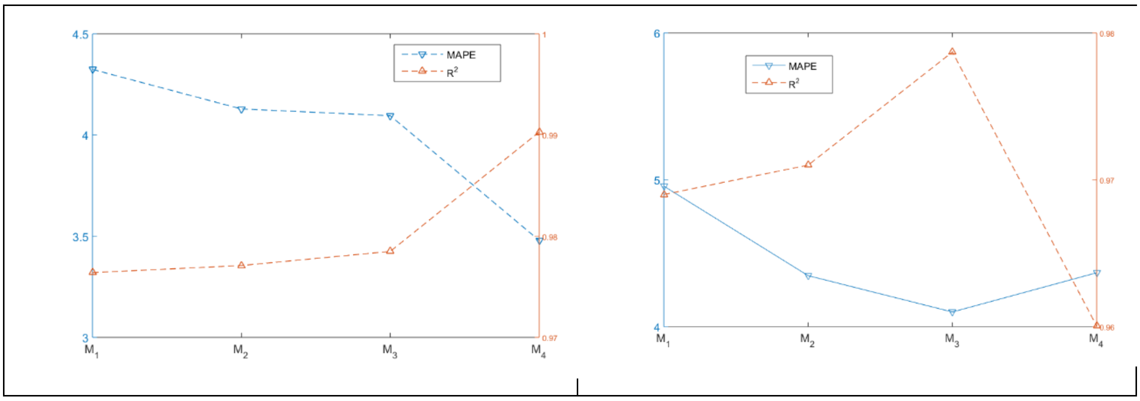

Figure 4-15. The performance of RNN on different data sets: (a) training (b) test.

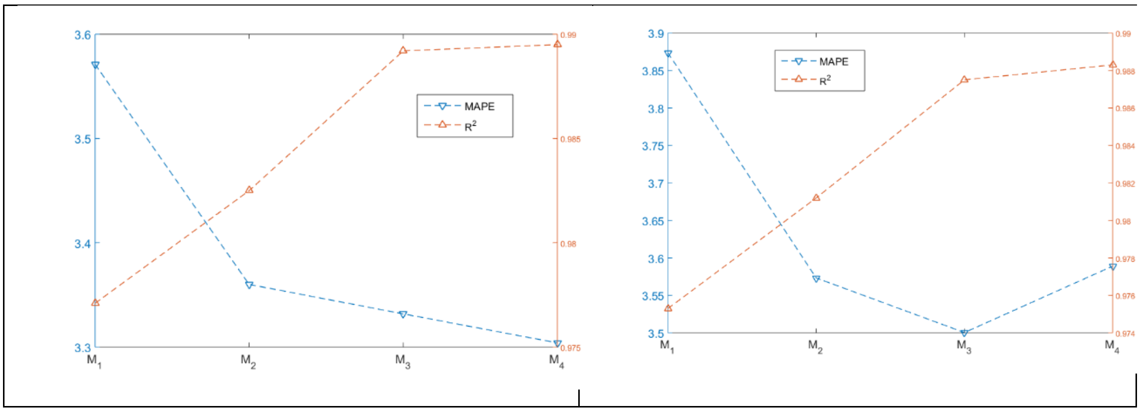

Figure 4-16. The performance of ANFIS on different data sets: (a) training (b) test.

The MAPE and R^2 of the three algorithms with four data sets with sizes of 250, 500, 750 and 1000 were determined. The results presented in Table 4-9 show that in the training phase, all algorithms performed better with increasing input dataset size. However, the test case error indicates that for the M_4 data set, FFNN and RNN suffered from overfitting, hence their results in the test phase were not promising. For these two algorithms, the M_3 data set presented the least testing MAPE error. While in the case of ANFIS, increasing the dataset size from 750 to 1000 improved algorithm performance for both training and testing cases. The improvement of M_4 was not significant compared to M_3, so to avoid excessive computational costs, the M_3 data set with a size of 750 samples was selected for building the ensemble algorithms. The computational time for each Metamodel approach (training and testing) are reported in Table 4-8 and the best training and testing performances of all algorithms are shown in bold font in Table 4-9.

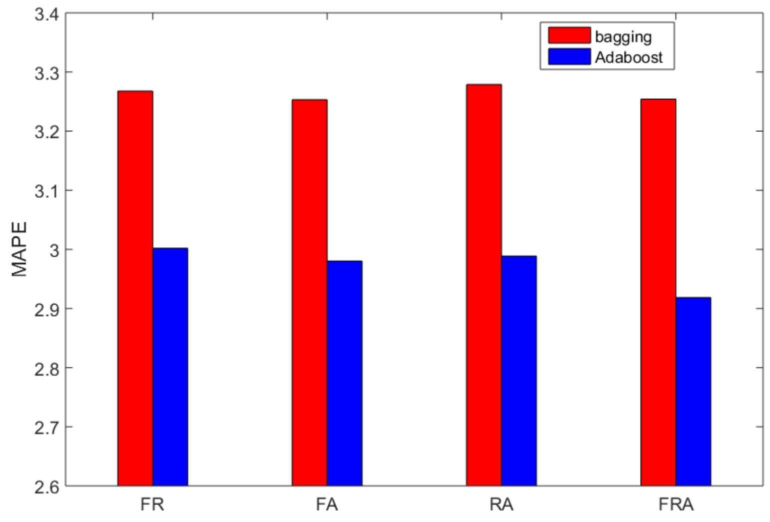

Figure 4-17. The MAPE of different ensembles on training phase.

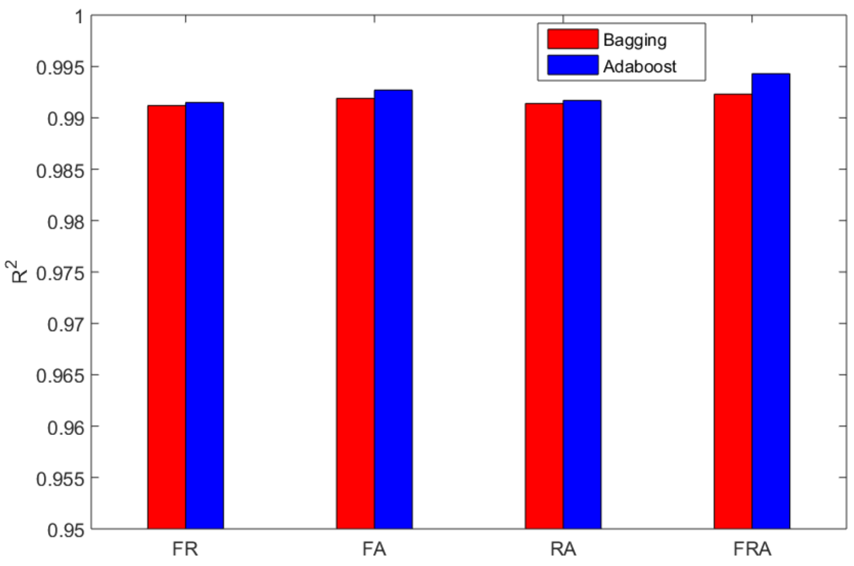

Figure 4-18. The R^2 of different ensembles on training phase.

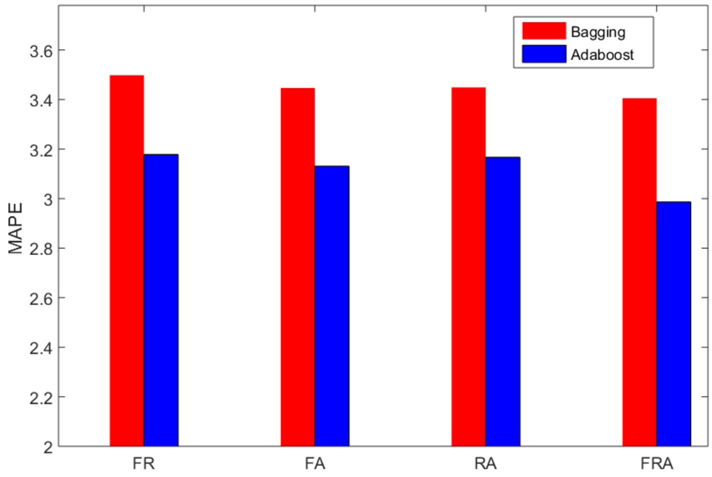

Figure 4-19. The MAPE of different ensembles on test phase.

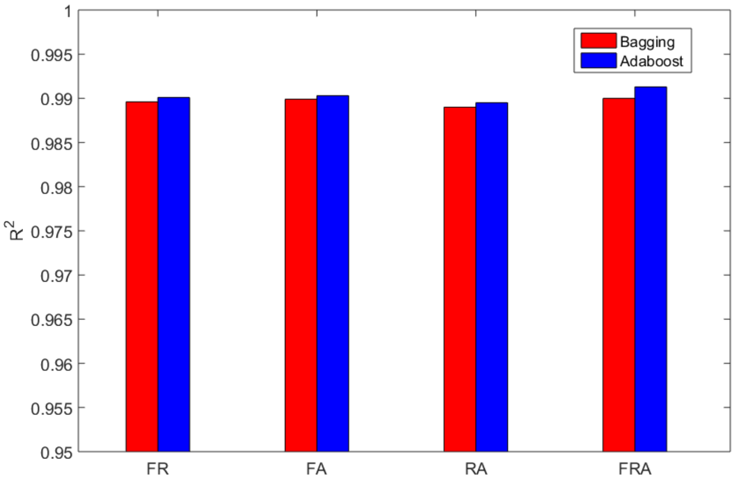

Figure 4-20. The R^2 of different ensembles on training phase.

Table 4-10. Performance of ensemble algorithms with testing data.

Ensemble		R^2		MAPE (%)	
		Training	Testing	Training	Testing
FR	Bagging	0.9912	0.9896	3.2678	3.4981
	AdaBoost	0.9915	0.9901	3.002	3.1782
FA	Bagging	0.9919	0.9899	3.2532	3.4467
	AdaBoost	0.9927	0.9903	2.9802	3.131
RA	Bagging	0.9914	0.9890	3.2789	3.4490
	AdaBoost	0.9917	0.9895	2.9887	3.1672
FRA	Bagging	0.9923	0.9900	3.2541	3.4056
	AdaBoost	0.9943	**0.9913**	2.9185	**2.9865**

For the Bagging ensemble, the training data set with 2000 samples was used to randomly create three 750-sample data sets using the sampling method with replacement.

For AdaBoost, one 750-sample data set was randomly chosen from the available training samples. The ensemble approach results are presented in Table 4-10. It is observed from these results that for all ensemble algorithms, AdaBoost outperformed Bagging in both training and testing phases. The least MAPE error was achieved for the AdaBoost ensemble of the three algorithms, i.e. FFNN, RNN and ANFIS. Moreover, the AdaBoost ensemble had the highest coefficient of determination (R^2).

4.6. Optimization approach

One of the benefits of using metamodels in these types of simulation-based optimizations is the possibility of using the same metamodel for various runs of optimization. Evolutionary algorithms always have a risk of trapping in local optima and they are not guarantee the optimum solution therefore, using a metamodel makes us able to test different algorithms. For instance, for a GA with 80 generations and initial population of 100 we need 8000 results from the simulation and for each result, we need 5 replications. Therefore, $80 \times 100 \times 5 = 40000$ runs is needed. Suppose that we need to run our GA for 10 times to choose the best solution out of them then this number will be doubled $40000 \times 10 = 400000$. We know that each simulation takes almost 1 minute therefore, we need 6666.67 hours or 277.78 days of CPU time for only GA.

In this study, three algorithms including GA, chaotic GA and ICA are selected to find the best resource plan to minimize the ALOS in ED. After several algorithm executions and observing the solution evaluation, the initial population for GA was set to 100 while the mutation and crossover rates were set to 10% and 75% respectively. The results show that the chance of improvement after 90 generations is low; therefore, 100 generations were selected as the termination criterion. This parameters setting is the same for both GA and chaotic GA. The results for ICA lead us to the initial population of 100 with 10 initial imperialists, and 10% of revolution rate.

Table 4-11. Comparison between baseline model and near-optimum resource planning from optimization approaches.

	Reception	Triage Room	Lab	Suturing			Yellow zone			Orthopedics		Pediatrics		Surgical emergency			Clinical emergency		
Variables	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}	x_{11}	x_{12}	x_{13}	x_{14}	x_{15}	x_{16}	x_{17}	x_{18}	x_{19}
Baseline	2	1	3	1	1	1	3	4	1	4	3	2	2	4	3	1	2	5	1
New	2	2	2	1	1	1	5	6	1	2	3	2	2	3	3	1	3	3	1

Table 4-11 shows a comparison of the current ED resource allocation with the results obtained from optimization approaches. There was no difference between the obtained results from all three approaches (GA, Chaotic GA and ICA). Therefore, the other aspects that can make an algorithm superior to the other ones are investigated.

The most significant difference between the approaches can be seen in their success rate. In order to compare the algorithms based on their success rate, all algorithms were run for 100 times and the number of runs with the best results were counted for each algorithm. Table 4-12 shows the computational time and success rate for each algorithm. Although ICA has better success rate, in computational time GA wins.

Table 4-12. Computational time and success rate for each algorithm.

Optimization approach	Computational time (seconds)	Success rate
GA	6.08612	18%
Chaotic GA	6.12704	26%
ICA	12.26679	67%

GA: Genetic Algorithm

ICA: Imperialist Competitive Algorithm

As mentioned before, because of the characteristics of at hand problem a metamodel approach is used. In this part, the result from the optimization is tested using the simulation model. To do so, the variables from Table 4-11 that are the results from our near-optima solution, are the input of the simulation. Then the result from simulation is compared with the result from the metamodel.

Table 4-13. The comparison of results from simulation and metamodel before/after optimization with baseline data.

No	Section	Actual time (baseline)	Simulation data (baseline)	Metamodel (optimization)	Simulation (optimization)
1	Suturing	196.45	202.40	208.20	199.3
2	Yellow zone	412.46	401.30	365	350.4
3	Orthopedics	180.45	192.60	236.80	247.45
4	Pediatrics	310.72	318.80	301.50	292.40
5	Surgical emergency	438.76	442.60	428.40	436.90
6	Clinical emergency	487.41	498.10	523.10	538.78
7	Total	328.728	319.143	274.04	279.52

The results from the current ED resource planning and near-optimum resource allocation from optimization approaches are compared in Figure 4-21. The patient ALOS with the new resource allocation shows a 14% reduction on average. Figure 4-22 shows the evaluation of two different runs of ICA to find the near optima solution.

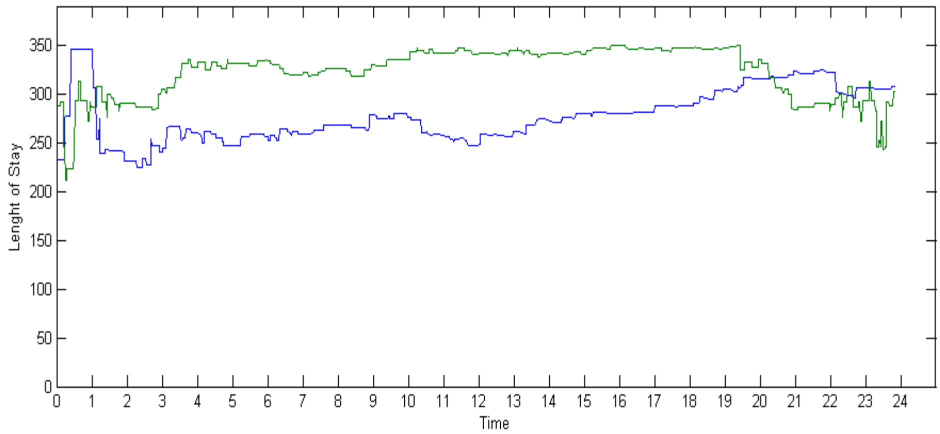

Figure 4-21. Length of stay for baseline resource allocation and the new resource allocation.

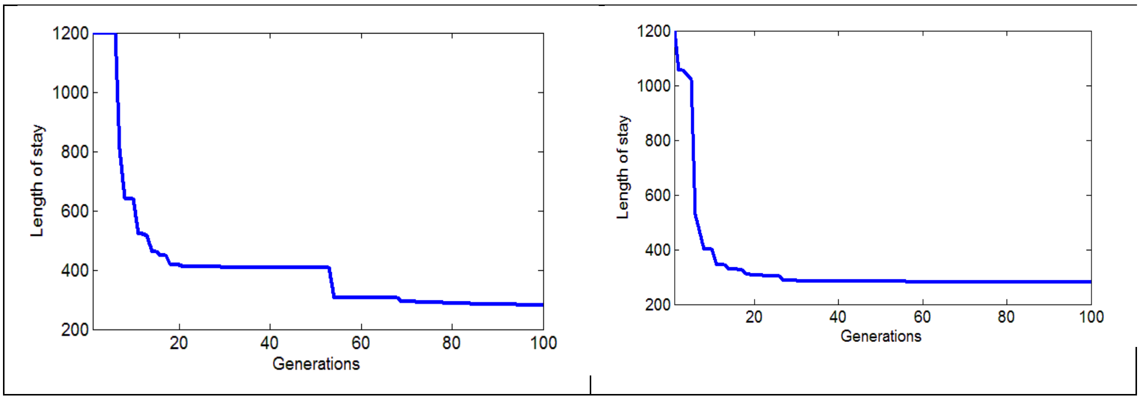

Figure 4-22. Evolution of ICA in finding near optima solution.

Chapter 5
Conclusion

The goal of this chapter is to summarize the achieved results from this study and to highlight the contributions of this thesis that was already mentioned in previous chapters. Then the limitations of this study and in general limitations of computer-based simulations studies in healthcare industry are discussed. The last part of this chapter contains several recommendations for further studies in future.

5.1. Summary of Research

The main objective of this study is to provide a decision support system for one of the most complex parts of healthcare industry. To provide a proper DSS, after reviewing the relevant literature and data collection, different computer tools including agent-based simulation, machine learnings, cellular automata and evolutionary algorithms were used.

EDs contain numerous human interactions and decisions that are made by humans. ABSs have shown their ability to simulate complex systems that have human behaviors. Therefore, in this study, an ABS approach is implemented to simulate EDs in macro and micro level. After studying the behavior of agents in ED, their characteristics were added to each type of agent using different tools such as Cellular Automata (CA). Afterwards, a similar discrete event case study from literature review was selected to implement the proposed ABS. The simulation was successfully done and the results were published in Brazilian Journal of Medical and Biological Research (Yousefi & Ferreira, 2017).

In the second part of this thesis, an ED in Belo Horizonte was selected. After data collection and studying behavior of the system an agent-based simulation was implemented using Netlogo 6.0. In order to improve the performance of the ED, different metamodeling approaches as well as optimization approaches were used to find a better resource allocation and reduce the average length of stay of patients in ED. Since the simulation has 19 decision variables, to avoid high computational times, FFNN, RNN and ANFIS were trained with four data sets with sizes of 250, 500, 750 and 1000 then their performances were tested on a set with size of 200. Later the results from metamodel were used as fitness function of evolutionary algorithms to evaluate the possible solutions. Three evolutionary algorithms including GA, chaotic GA and Ica were implemented to find a near optimum resource allocation.

5.2. Limitations of the Study

Limitations are avoidable and possible to be controlled. However, there are limitations to all forms of research. Here we list some of the limitations of this study.

- To simulate human behavior properly we need to access to more data to extract human behavior from them. Furthermore, we had access to only one ED, consequently our DSS is limited to only one ED.
- Except for few researches in Portuguese, this study is limited to English language research studies.
- This study is limited to simulating an ED in normal conditions. We did not consider any disaster conditions.

5.3. Discussion and Interpretation of Findings

The first part of this study proves that implementing a group decision making (self-organizing) in an ED, helps the system to use its resources in a better way. Scenario 1 has the highest change rate with applying self-organizing and its ALOS and total waiting time are reduced by 15.3% and 24.25 respectively, while the total reduction in all cases for ALOS was 6.8% and for waiting time was 12.70%. Furthermore, the improvement in LWBS, and the total output of the ED was reported.

Based on our literature review, this study is the first application of Cellular Automata (CA) in this field of study. CA are strong tools to simulate behavior of human in any queuing problem. In classical queuing problems, agents decide to stay in a queue only based on the time that they already spent there. In fact, CA assist developers to make agents with higher level of intelligence and that makes them able to have better tools to simulate complex dynamic systems. The proposed CA in this study can be easily adapted for other relevant simulation studies.

Resource allocation as the process of assigning resources in an ED is a difficult task for different reasons such as shortage in budgets and operating 24/7. When the economic condition is worse, the importance of resource allocation is even more obvious. In the second part of this study, we try to implement our proposed DSS in a real world case study from Risoleta Tolentino Neves Emergency Department in Belo Horizonte to find a better resource allocation. One of the most common KPIs in healthcare industry studies is average length of stay (ALOS) of patients. Because the more patients spend time in the system, the more resources that they need increase. Moreover, the possibility of leaving without being seen will increase. The other reason for choosing ALOS in this study was the possibility of validating our results. Because as mentioned before, the related data to ALOS are recorded in Hospital. Therefore, ALOS was selected as the main KPI and the objective of this part was set on choosing the best resource allocation to decrease ALOS.

Because of the complexity of the simulation model and number of decision variables having an exhaustive search to find the best resource allocation is computationally expensive, to cope with this problem a robust approximation model to find relationships between the inputs and outputs of the proposed DSS was applied. The metamodel is created with an ensemble of the adaptive neuro-fuzzy inference system (ANFIS), feedforward neural network (FFNN) and recurrent neural network (RNN) using the adaptive boosting (AdaBoost) ensemble algorithm. The proposed metamodel shows a 26.6% improvement compared to the average results of ANFIS, FFNN and RNN in terms of mean absolute percentage error (MAPE).

To tackle the resource allocation optimization problem two evolutionary algorithms including GA and ICA were used; GA as the most common evolutionary algorithm that is based on mimicking biological evolution and ICA as a relevantly new algorithm that can be considered as the social counterpart of GAs. Moreover, to avoid GA trapping in local optima a chaotic GA is implemented. The results from three algorithms show that all of them can reach to the same point at their best performance that is able to decrease the ALOS in this ED case study by 14%. Comparing success rates of the algorithms shows that ICA has the highest success rate with 67% and GA has the lowest with 18% while the success rate for chaotic GA was 26%.

Simulations give us an opportunity to investigate the behavior of the system and find its drawbacks and try to solve them. This simulation shows that two bottlenecks of this system are Triage Room and Yellow zone. Shortage in number of Triage Nurses causes long length of stay and it increases patients' dissatisfaction. That can make them leave the ED without being treated.

5.4. Further Research

This section presents some recommendations for future studies. Some of them are the future studies of the author.

- In this thesis, we developed agents with the ability of group decision making (self-organizing) in an ED. Using a simple mobile application or any other instrument can make it possible in real world case studies. ED's staff receive information about length of queue etc. Then they take part in a group decision making to re-allocate the resources. Afterwards, the results from simulation can be compared with the real case.

- Another future research can concentrate on sensitivity analysis of different variables in ED.

- The same metamodeling approach from this thesis can be applied in any forecasting or metamodeling problems such as forecasting number of daily visits to an ED.

- Integrating simulation with forecasting would help the ED's managers to decide about resource allocation of the ED at least few days in advance. In general, input of simulation is based on past data. In this approach the results of forecasting will be used as input of simulation.

- In this thesis, we assumed that ED is separated from hospital. We did not consider the connections of ED and hospital in simulation. A future study can connect the ED with hospital.

- Future studies can add more details to their agents. For instance, agents will be able to transfer influenza-like viruses in ED.

References

Abo-Hamad, W., & Arisha, A. (2013). Simulation-based framework to improve patient experience in an emergency department. *European Journal of Operational Research*, *224*(1), 154-166.

Aboukanda, E., & Latif, M. (2013). Exploiting simulation to reduce patient waiting time using a streaming strategy in an emergency department. *International Journal of Advanced Technology & Engineering Research, 3*(2), 79-86.

Ahalt, V., Argon, N. T., Ziya, S., Strickler, J., & Mehrotra, A. (2016). Comparison of emergency department crowding scores: a discrete-event simulation approach. *Health Care Management Science*, 1-12.

Ahmed, M. A., & Alkhamis, T. M. (2009). Simulation optimization for an emergency department healthcare unit in Kuwait. *European Journal of Operational Research*, *198*(3), 936-942. doi:http://dx.doi.org/10.1016/j.ejor.2008.10.025

Ahn, H. J., & Lee, H. (2004). An agent-based dynamic information network for supply chain management. *BT Technology Journal, 22*(2), 18-27.

Ajami, S., Ketabi, S., Yarmohammadian, M. H., & Bagherian, H. (2012). Wait time in emergency department (ED) processes. *Medical Archives, 66*(1), 53.

Akanle, O., & Zhang, D. (2008). Agent-based model for optimising supply-chain configurations. *International Journal of Production Economics, 115*(2), 444-460.

Al-Kattan, I. (2009). DISASTER RECOVERY PLAN DEVELOPMENT FOR THE EMERGENCYDEPARTMENT-CASE STUDY. *Public Administration and Management*, *14*(1), 75.

Al-Refaie, A., Fouad, R. H., Li, M.-H., & Shurrab, M. (2014). Applying simulation and DEA to improve performance of emergency department in a Jordanian hospital. *Simulation Modelling Practice and Theory, 41*, 59-72.

Asplin, B. R., Magid, D. J., Rhodes, K. V., Solberg, L. I., Lurie, N., & Camargo, C. A. (2003). A conceptual model of emergency department crowding. *Annals of Emergency Medicine, 42*(2), 173-180.

Atashpaz-Gargari, E., & Lucas, C. (2007). *Imperialist competitive algorithm: an algorithm for optimization inspired by imperialistic competition.* Paper presented at the Evolutionary computation, 2007. CEC 2007. IEEE Congress on.

Axelrod, R. M. (1997). *The complexity of cooperation: Agent-based models of competition and collaboration*: Princeton University Press.

Azadeh, A., Rouhollah, F., Davoudpour, F., & Mohammadfam, I. (2013). Fuzzy modelling and simulation of an emergency department for improvement of nursing schedules with noisy and uncertain inputs. *International Journal of Services and Operations Management, 15*(1), 58-77.

Baesler, F. F., Jahnsen, H. E., & DaCosta, M. (2003). *Emergency departments I: the use of simulation and design of experiments for estimating maximum capacity in an emergency room.* Paper presented at the Proceedings of the 35th conference on Winter simulation: driving innovation.

Banks, J. (1998). *Handbook of simulation: principles, methodology, advances, applications, and practice*: John Wiley & Sons.

Barton, R. R., & Meckesheimer, M. (2006). Metamodel-based simulation optimization. *Handbooks in operations research and management science, 13*, 535-574.

Batarseh, O. G., Goldlust, E. J., & Day, T. E. (2013). *SysML for conceptual modeling and simulation for analysis: a case example of a highly granular model of an emergency department.* Paper presented at the Simulation Conference (WSC), 2013 Winter.

Billari, F. C. (2006). *Agent-based computational modelling: applications in demography, social, economic and environmental sciences*: Taylor & Francis.

Blasak, R. E., Starks, D. W., Armel, W. S., & Hayduk, M. C. (2003). *Healthcare process analysis: the use of simulation to evaluate hospital operations between the emergency department and a medical telemetry unit.* Paper presented at the Proceedings of the 35th conference on Winter simulation: driving innovation.

Bonabeau, E. (2002). Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the National Academy of Sciences, 99*(suppl 3), 7280-7287.

Bowers, J., Ghattas, M., & Mould, G. (2009). Success and failure in the simulation of an Accident and Emergency department. *Journal of simulation, 3*(3), 171-178.

Bowers, J., & Mould, G. (2013). Understanding the effects of service redesign on patient-time in an emergency department. *International Journal of Services Technology and Management, 19*(4-6), 254-266.

Boyacioglu, M. A., & Avci, D. (2010). An adaptive network-based fuzzy inference system (ANFIS) for the prediction of stock market return: the case of the Istanbul stock exchange. *Expert Systems with Applications, 37*(12), 7908-7912.

Breiman, L. (1996). Bagging predictors. *Machine learning, 24*(2), 123-140.

Brenner, S., Zeng, Z., Liu, Y., Wang, J., Li, J., & Howard, P. K. (2010). Modeling and analysis of the emergency department at University of Kentucky Chandler Hospital using simulations. *Journal of Emergency Nursing, 36*(4), 303-310.

Cabrera, E., Luque, E., Taboada, M., Epelde, F., & Iglesias, M. L. (2012). *ABMS optimization for emergency departments.* Paper presented at the Proceedings of the winter simulation conference.

Cabrera, E., Taboada, M., Iglesias, M. L., Epelde, F., & Luque, E. (2011). Optimization of healthcare emergency departments by agent-based simulation. *Procedia computer science, 4*, 1880-1889.

Cao, H., & Huang, S. (2012). Principles of scarce medical resource allocation in natural disaster relief: a simulation approach. *Medical Decision Making, 32*(3), 470-476.

Cardoen, B., Demeulemeester, E., & Beliën, J. (2010). Operating room planning and scheduling: A literature review. *European Journal of Operational Research, 201*(3), 921-932.

Caridi, M., & Cavalieri, S. (2004). Multi-agent systems in production planning and control: an overview. *Production Planning & Control, 15*(2), 106-118.

Chiavone, P. A., & Sens, Y. A. d. S. (2003). Evaluation of APACHE II system among intensive care patients at a teaching hospital. *Sao Paulo Medical Journal, 121*(2), 53-57.

Chiu, S. L. (1994). Fuzzy model identification based on cluster estimation. *Journal of Intelligent & fuzzy systems, 2*(3), 267-278.

Chockalingam, A., Jayakumar, K., & Lawley, M. A. (2010). *A stochastic control approach to avoiding emergency department overcrowding.* Paper presented at the Simulation Conference (WSC), Proceedings of the 2010 Winter.

Choon, O. H., Dali, Z., Beng, P. T., & Magdalene, C. P. Y. (2014). Uncovering effective process improvement strategies in an emergency department using discrete event simulation. *Health Systems, 3*(2), 93-104.

Cioppa, T. M. (2002). *Efficient nearly orthogonal and space-filling experimental designs for high-dimensional complex models*. Retrieved from

Coelho, L. d. S. (2008). A quantum particle swarm optimizer with chaotic mutation operator. *Chaos, Solitons & Fractals, 37*(5), 1409-1418. doi:http://dx.doi.org/10.1016/j.chaos.2006.10.028

Connelly, L. G., & Bair, A. E. (2004). Discrete event simulation of emergency department activity: A platform for system-level operations research. *Academic Emergency Medicine, 11*(11), 1177-1185.

Conte, R., Hegselmann, R., & Terna, P. (1997). Introduction: Social simulation—a new disciplinary synthesis *Simulating Social Phenomena* (pp. 1-17): Springer.

Damousis, I. G., & Dokopoulos, P. (2001). *A fuzzy expert system for the forecasting of wind speed and power generation in wind farms.* Paper presented at the Power Industry Computer Applications, 2001. PICA 2001. Innovative Computing for Power-Electric Energy Meets the Market. 22nd IEEE Power Engineering Society International Conference on.

Davies, R. (2007). *"See and Treat" or "See" and "Treat" in an emergency department.* Paper presented at the Simulation Conference, 2007 Winter.

Day, T. E., Al-Roubaie, A. R., & Goldlust, E. J. (2012). Decreased length of stay after addition of healthcare provider in emergency department triage: a comparison between computer-simulated and real-world interventions. *Emergency Medicine Journal*, emermed-2012-201113.

Derlet, R. W., & Richards, J. R. (2000). Overcrowding in the nation's emergency departments: complex causes and disturbing effects. *Annals of Emergency Medicine, 35*(1), 63-68.

Diefenbach, M., & Kozan, E. (2011). Effects of bed configurations at a hospital emergency department. *Journal of simulation, 5*(1), 44-57.

Dietterich, T. G. (2000). *Ensemble methods in machine learning.* Paper presented at the International workshop on multiple classifier systems.

Duguay, C., & Chetouane, F. (2007). Modeling and improving emergency department systems using discrete event simulation. *SIMULATION, 83*(4), 311-320.

Eatock, J., Clarke, M., Picton, C., & Young, T. (2011). Meeting the four-hour deadline in an A&E department. *Journal of health organization and management, 25*(6), 606-624.

Eddy, D. M., Hollingworth, W., Caro, J. J., Tsevat, J., McDonald, K. M., & Wong, J. B. (2012). Model transparency and validation: a report of the ISPOR-SMDM Modeling Good Research Practices Task Force–7. *Medical Decision Making, 32*(5), 733-743.

Elman, J. L. (1990). Finding structure in time. *Cognitive science, 14*(2), 179-211.

Engelmore, R., & Morgan, A. (1988). Blackboard Systems. The Insight Series in Aritificial Intelligence: Addison-Wesley.

Eskandari, H., Riyahifard, M., Khosravi, S., & Geiger, C. D. (2011). *Improving the emergency department performance using simulation and MCDM methods.* Paper presented at the Simulation Conference (WSC), Proceedings of the 2011 Winter.

Fletcher, A., Halsall, D., Huxham, S., & Worthington, D. (2016). The DH Accident and Emergency Department Model: A National Generic Model Used Locally *Operational Research for Emergency Planning in Healthcare: Volume 2* (pp. 71-91): Springer.

Fone, D., Hollinghurst, S., Temple, M., Round, A., Lester, N., Weightman, A., . . . Palmer, S. (2003). Systematic review of the use and value of computer simulation modelling in population health and health care delivery. *Journal of Public Health, 25*(4), 325-335.

Forget, P., D'Amours, S., & Frayret, J.-M. (2008). Multi-behavior agent model for planning in supply chains: An application to the lumber industry. *Robotics and Computer-Integrated Manufacturing, 24*(5), 664-679.

Forster, A. J., Stiell, I., Wells, G., Lee, A. J., & Van Walraven, C. (2003). The effect of hospital occupancy on emergency department length of stay and patient disposition. *Academic Emergency Medicine, 10*(2), 127-133.

Frayret, J.-M., D'Amours, S., Rousseau, A., Harvey, S., & Gaudreault, J. (2007). Agent-based supply-chain planning in the forest products industry. *International Journal of Flexible Manufacturing Systems, 19*(4), 358-391.

Freund, Y., Schapire, R., & Abe, N. (1999). A short introduction to boosting. *Journal-Japanese Society For Artificial Intelligence, 14*(771-780), 1612.

Fruggiero, F., Lambiase, A., & Fallon, D. (2008). Computer simulation and swarm intelligence organisation into an emergency department: a balancing approach across ant colony optimisation. *International Journal of Services Operations and Informatics, 3*(2), 142-161.

Fu, M. C. (2002). Optimization for simulation: Theory vs. practice. *INFORMS Journal on Computing, 14*(3), 192-215.

Fu, M. C., Glover, F. W., & April, J. (2005). *Simulation optimization: a review, new developments, and applications.* Paper presented at the Simulation Conference, 2005 Proceedings of the Winter.

Fu, M. C., & Hu, J.-Q. (1995). Sensitivity analysis for Monte Carlo simulation of option pricing. *Probability in the Engineering and Informational Sciences, 9*(03), 417-446.

Ghanes, K., Wargon, M., Jouini, O., Jemai, Z., Diakogiannis, A., Hellmann, R., . . . Koole, G. (2015). Simulation-based optimization of staffing levels in an emergency department. *SIMULATION*, 942–953.

Giannakis, M., & Louis, M. (2011). A multi-agent based framework for supply chain risk management. *Journal of Purchasing and Supply Management, 17*(1), 23-31.

Goldsman, D., Nance, R. E., & Wilson, J. R. (2009). *A brief history of simulation.* Paper presented at the Winter Simulation Conference.

Gosavi, A. (2003). Simulation-based optimization. *parametric optimization techniques and reinforcement learning*.

Gul, M., & Guneri, A. F. (2012). A computer simulation model to reduce patient length of stay and to improve resource utilization rate in an emergency department service system. *International Journal of Industrial Engineering, 19*(5), 221-231.

Gul, M., & Guneri, A. F. (2015). A comprehensive review of emergency department simulation applications for normal and disaster conditions. *Computers & Industrial Engineering, 83*, 327-344.

Gunal, M. M. (2012). A guide for building hospital simulation models. *Health Systems, 1*(1), 17-25.

Gunal, M. M., & Pidd, M. (2006). *Understanding accident and emergency department performance using simulation.* Paper presented at the Proceedings of the 38th conference on Winter simulation.

Gurkan, G., Ozge, A. Y., & Robinson, T. (1994). *Sample-path optimization in simulation.* Paper presented at the Simulation Conference Proceedings, 1994. Winter.

Hachicha, W., Ammeri, A., Masmoudi, F., & Chachoub, H. (2010). A comprehensive literature classification of simulation optimisation methods.

Han, J. H., Zhou, C., France, D. J., Zhong, S., Jones, I., Storrow, A. B., & Aronsky, D. (2007). The effect of emergency department expansion on emergency department overcrowding. *Academic Emergency Medicine, 14*(4), 338-343.

Hansen, L. K., & Salamon, P. (1990). Neural network ensembles. *IEEE transactions on pattern analysis and machine intelligence, 12*, 993-1001.

Head, B., Hjorth, A., Brady, C., & Wilensky, U. (2015). *Evolving agent cognition with Netlogo LevelSpace.* Paper presented at the Winter Simulation Conference (WSC), 2015.

Herrera-Viedma, E., Martinez, L., Mata, F., & Chiclana, F. (2005). A consensus support system model for group decision-making problems with multigranular linguistic preference relations. *IEEE Transactions on fuzzy Systems, 13*(5), 644-658.

Holland, J. H. (1975). *Adaptation in natural and artificial systems: an introductory analysis with applications to biology, control, and artificial intelligence*: U Michigan Press.

Holm, L. B., & Dahl, F. A. (2009). *Simulating the effect of physician triage in the emergency department of Akershus University Hospital.* Paper presented at the Winter Simulation Conference.

Holm, L. B., & Dahl, F. A. (2010). *Simulating the influence of a 45% increase in patient volume on the emergency department of Akershus University Hospital.* Paper presented at the Proceedings of the Winter Simulation Conference.

Hoot, N. R., LeBlanc, L. J., Jones, I., Levin, S. R., Zhou, C., Gadd, C. S., & Aronsky, D. (2008). Forecasting emergency department crowding: a discrete event simulation. *Annals of Emergency Medicine, 52*(2), 116-125.

Iman, R. L. (2008). Latin hypercube sampling. *Encyclopedia of quantitative risk analysis and assessment*.

Iman, R. L., & Conover, W. (1980). Small sample sensitivity analysis techniques for computer models. with an application to risk assessment. *Communications in statistics-theory and methods, 9*(17), 1749-1842.

Ismail, K., Abo-Hamad, W., & Arisha, A. (2010). *Integrating balanced scorecard and simulation modeling to improve emergency department performance in Irish hospitals.* Paper presented at the Simulation Conference (WSC), Proceedings of the 2010 Winter.

Izady, N., & Worthington, D. (2012). Setting staffing requirements for time dependent queueing networks: The case of accident and emergency departments. *European Journal of Operational Research, 219*(3), 531-540.

Jacobson, S. H., Hall, S. N., & Swisher, J. R. (2006). Discrete-event simulation of health care systems *Patient flow: Reducing delay in healthcare delivery* (pp. 211-252): Springer.

Jang, J.-S. (1993). ANFIS: adaptive-network-based fuzzy inference system. *IEEE transactions on systems, man, and cybernetics, 23*(3), 665-685.

Jerbi, B., & Kamoun, H. (2009). Using simulation and goal programming to reschedule emergency department doctors' shifts: case of a Tunisian hospital. *Journal of simulation, 3*(4), 211-219.

Joshi, A. J. (2008). *Study on the effect of different arrival patterns on an emergency department's capacity using discrete event simulation.* Citeseer.

Jovanović, R. Ž., Sretenović, A. A., & Živković, B. D. (2015). Ensemble of various neural networks for prediction of heating energy consumption. *Energy and Buildings, 94*, 189-199.

Jun, J., Jacobson, S. H., & Swisher, J. (1999). Application of discrete-event simulation in health care clinics: A survey. *Journal of the operational research society, 50*(2), 109-123.

Kadri, F., Chaabane, S., & Tahon, C. (2014). A simulation-based decision support system to prevent and predict strain situations in emergency department systems. *Simulation Modelling Practice and Theory, 42*, 32-52.

Kaihara, T. (2003). Multi-agent based supply chain modelling with dynamic environment. *International Journal of Production Economics*, *85*(2), 263-269.

Karageorgos, A., Mehandjiev, N., Weichhart, G., & Hämmerle, A. (2003). Agent-based optimisation of logistics and production planning. *Engineering Applications of Artificial Intelligence, 16*(4), 335-348.

Kazem, A., Sharifi, E., Hussain, F. K., Saberi, M., & Hussain, O. K. (2013). Support vector regression with chaos-based firefly algorithm for stock market price forecasting. *Applied soft computing, 13*(2), 947-958.

Kazemi, A., & Zarandi, M. F. (2008). An agent-based framework for building decision support system in supply chain management. *Journal of Applied Sciences, 8*(7), 1125-1137.

Khare, R. K., Powell, E. S., Reinhardt, G., & Lucenti, M. (2009). Adding more beds to the emergency department or reducing admitted patient boarding times: which has a more significant influence on emergency department congestion? *Annals of Emergency Medicine, 53*(5), 575-585. e572.

Khurma, N., Bacioiu, G. M., & Pasek, Z. J. (2008). *Simulation-based verification of lean improvement for emergency room process.* Paper presented at the Proceedings of the 40th conference on winter simulation.

Kim, P., & Ding, Y. (2005). Optimal engineering system design guided by data-mining methods. *Technometrics, 47*(3), 336-348.

Kirtland, A., Lockwood, J., Poisker, K., Stamp, L., & Wolfe, P. (1995). *Simulating an emergency department" is as much fun as...".* Paper presented at the Simulation Conference Proceedings, 1995. Winter.

Kleijnen, J. P. (1975). A comment on Blanning's "Metamodel for sensitivity analysis: the regression metamodel in simulation". *Interfaces, 5*(3), 21-23.

Kleijnen, J. P., & Sargent, R. G. (2000). A methodology for fitting and validating metamodels in simulation. *European Journal of Operational Research, 120*(1), 14-29.

Knaus, W. A., Draper, E. A., Wagner, D. P., & Zimmerman, J. E. (1985). APACHE II: a severity of disease classification system. *Critical care medicine, 13*(10), 818-829.

Kohler, T. A., Gumerman, G. J., & Reynolds, R. G. (2005). Simulating ancient societies. *Scientific American, 293*(1), 76-84.

Kolb, E. M., Lee, T., & Peck, J. (2007). *Effect of coupling between emergency department and inpatient unit on the overcrowding in emergency departmetn.* Paper presented at the Simulation Conference, 2007 Winter.

Kolker, A. (2008). Process modeling of emergency department patient flow: Effect of patient length of stay on ED diversion. *Journal of medical systems, 32*(5), 389-401.

Konrad, R., DeSotto, K., Grocela, A., McAuley, P., Wang, J., Lyons, J., & Bruin, M. (2013). Modeling the impact of changing patient flow processes in an emergency department: Insights from a computer simulation study. *Operations Research for Health Care, 2*(4), 66-74.

Kumar, A., & Mo, J. (2010). *Models for bed occupancy management of a hospital in Singapore*. Paper presented at the Proceedings of the 2010 International Conference on Industrial Engineering and Operations Management.

Law, A. M. (2014). *A tutorial on design of experiments for simulation modeling*. Paper presented at the Proceedings of the 2014 Winter Simulation Conference.

Liang, W.-Y., & Huang, C.-C. (2006). Agent-based demand forecast in multi-echelon supply chain. *Decision Support Systems, 42*(1), 390-407.

Lin, F.-r., & Lin, Y.-y. (2007). Integrating multi-agent negotiation to resolve constraints in fulfilling supply chain orders. *Electronic Commerce Research and Applications, 5*(4), 313-322.

Liu, H., Tian, H.-q., Li, Y.-f., & Zhang, L. (2015). Comparison of four Adaboost algorithm based artificial neural networks in wind speed predictions. *Energy Conversion and Management, 92*, 67-81.

Liu, S. W., Hamedani, A. G., Brown, D. F., Asplin, B., & Camargo Jr, C. A. (2013). Established and novel initiatives to reduce crowding in emergency departments. *Western Journal of Emergency Medicine, 14*(2).

Liu, Z., Cabrera, E., Rexachs, D., & Luque, E. (2014). *A generalized agent-based model to simulate emergency departments*. Paper presented at the In The Sixth International Conference on Advances in System Simulation.

Macal, C. M., & North, M. J. (2010). Tutorial on agent-based modelling and simulation. *Journal of simulation, 4*(3), 151-162.

Mackway-Jones, K., Marsden, J., & Windle, J. (2014). *Emergency triage: Manchester Triage Group* (3rd ed.). United Kingdom: John Wiley & Sons, Ltd.

Mandahawi, N., Al-Shihabi, S., Abdallah, A. A., & Alfarah, Y. M. (2010). Reducing waiting time at an emergency department using design for Six Sigma and discrete event simulation. *International Journal of Six Sigma and Competitive Advantage, 6*(1-2), 91-104.

Maull, R. S., Smart, P., Harris, A., & Karasneh, A. A.-F. (2009). An evaluation of ‘fast track’in A&E: a discrete event simulation approach. *The Service Industries Journal, 29*(7), 923-941.

McGuire, F. (1994). *Using simulation to reduce length of stay in emergency departments*. Paper presented at the Simulation Conference Proceedings, 1994. Winter.

McKay MD, B. R., Conover WJ. (1979). A comparison of three methods for selecting values of input variables from a computer code. *Technometrics, 21*, 7.

Medeiros, D. J., Swenson, E., & DeFlitch, C. (2008). *Improving patient flow in a hospital emergency department*. Paper presented at the Proceedings of the 40th Conference on Winter Simulation.

Mele, F. D., Guillén, G., Espuna, A., & Puigjaner, L. (2007). An agent-based approach for supply chain retrofitting under uncertainty. *Computers & chemical engineering, 31*(5), 722-735.

Mikolov, T., Karafiát, M., Burget, L., Cernocký, J., & Khudanpur, S. (2010). *Recurrent neural network based language model*. Paper presented at the Interspeech.

Miller, M. J., Ferrin, D. M., & Messer, M. G. (2004). *Fixing the emergency department: A transformational journey with EDSIM*. Paper presented at the Proceedings of the 36th conference on Winter simulation.

Moore, J. C., Boone, R. B., Koyama, A., & Holfelder, K. (2014). Enzymatic and detrital influences on the structure, function, and dynamics of spatially-explicit model ecosystems. *Biogeochemistry, 117*(1), 205-227.

Mould, G., Bowers, J., Dewar, C., & McGugan, E. (2016). Assessing the Impact of Systems Modeling in the Redesign of an Emergency Department *Operational Research for Emergency Planning in Healthcare: Volume 2* (pp. 31-47): Springer.

Mustafee, N., Katsaliaki, K., Gunasekaran, A., Williams, M. D., Chahal, K., Eldabi, T., & Young, T. (2013). A conceptual framework for hybrid system dynamics and discrete event simulation for healthcare. *Journal of Enterprise Information Management, 26*(1/2), 50-74.

Olshaker, J. S., & Rathlev, N. K. (2006). Emergency department overcrowding and ambulance diversion: the impact and potential solutions of extended boarding of admitted patients in the emergency department. *The Journal of emergency medicine, 30*(3), 351-356.

Pan, A., Leung, S., Moon, K., & Yeung, K. (2009). Optimal reorder decision-making in the agent-based apparel supply chain. *Expert Systems with Applications, 36*(4), 8571-8581.

Pan, X., Han, C. S., Dauber, K., & Law, K. H. (2007). A multi-agent based framework for the simulation of human and social behaviors during emergency evacuations. *Ai & Society, 22*(2), 113-132.

Park, E. H., Park, J., Ntuen, C., Kim, D., & Johnson, K. (2008). Forecast driven simulation model for service quality improvement of the emergency department in the Moses H. Cone Memorial Hospital. *Asian Journal on Quality, 9*(3), 1-14.

Patvivatsiri, L. (2006). *A simulation model for bioterrorism preparedness in an emergency room.* Paper presented at the Proceedings of the 38th conference on Winter simulation.

Peck, J. S., & Kim, S.-G. (2010). Improving patient flow through axiomatic design of hospital emergency departments. *CIRP Journal of Manufacturing Science and Technology, 2*(4), 255-260.

Plambeck, E. L., Fu, B.-R., Robinson, S. M., & Suri, R. (1993). *Throughput optimization in tandem production lines via nonsmooth programming.* Paper presented at the Proceedings of the 1993 Summer Computer Simulation Conference.

Powell, E., Khare, R., & Reinhardt, G. (2007). 223: Using Computer Simulation to Evaluate the Effect of Point-of-Care Testing on Emergency Department Patient Flow. *Annals of Emergency Medicine, 50*(3), S70.

Rado, O., Lupia, B., Leung, J. M., Kuo, Y.-H., & Graham, C. A. (2014). *Using simulation to analyze patient flows in a hospital emergency department in Hong Kong.* Paper presented at the Proceedings of the International Conference on Health Care Systems Engineering.

Ren, Y., Suganthan, P., & Srikanth, N. (2015). Ensemble methods for wind and solar power forecasting—A state-of-the-art review. *Renewable and Sustainable Energy Reviews, 50*, 82-91.

Rico, F., Salari, E., & Centeno, G. (2007). *Emergency departments nurse allocation to face a pandemic influenza outbreak.* Paper presented at the Simulation Conference, 2007 Winter.

Ruohonen, T., Neittaanmäki, P., & Teittinen, J. (2006). *Simulation model for improving the operation of the emergency department of special health care.* Paper presented at the Proceedings of the 38th conference on Winter simulation.

Ruszczyński, A., & Shapiro, A. (2003). Stochastic programming models. *Handbooks in operations research and management science, 10*, 1-64.

Sahu, A., Runger, G., & Apley, D. (2011). *Image denoising with a multi-phase kernel principal component approach and an ensemble version.* Paper presented at the 2011 IEEE Applied Imagery Pattern Recognition Workshop (AIPR).

Samaha, S., Armel, W. S., & Starks, D. W. (2003). *Emergency departments I: the use of simulation to reduce the length of stay in an emergency department.* Paper presented at the Proceedings of the 35th conference on Winter simulation: driving innovation.

Sankaranarayanan, K., Delgado, C., van Ackere, A., & Larsen, E. R. (2014). The micro-dynamics of queuing: understanding the formation of queues. *Journal of simulation, 8*(4), 304-313.

Seila, A. F., & Brailsford, S. (2009). Opportunities and challenges in health care simulation *Advancing the Frontiers of Simulation* (pp. 195-229): Springer.

Semini, M., Fauske, H., & Strandhagen, J. O. (2006). *Applications of discrete-event simulation to support manufacturing logistics decision-making: a survey.* Paper presented at the Simulation Conference, 2006. WSC 06. Proceedings of the Winter.

Sengupta, S., Deneweth, M., & Van Til, R. P. (2011). *A better approach to modeling emergency care service.* Paper presented at the Proceedings of the winter simulation conference.

Setijono, D., Mohajeri Naraghi, A., & Pavan Ravipati, U. (2010). Decision support system and the adoption of lean in a swedish emergency ward: balancing supply and demand towards improved value stream. *International Journal of lean six sigma, 1*(3), 234-248.

Shaikh, S. B., Jerrard, D. A., Witting, M. D., Winters, M. E., & Brodeur, M. N. (2012). How long are patients willing to wait in the emergency department before leaving without being seen? *Western Journal of Emergency Medicine, 13*(6).

Shen, W., Wang, L., & Hao, Q. (2006). Agent-based distributed manufacturing process planning and scheduling: a state-of-the-art survey. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews), 36*(4), 563-577.

Spedding, T. (2008). *Modelling patient arrivals when simulating an accident and emergency unit.* Paper presented at the Simulation Conference, 2008. WSC 2008. Winter.

Stein, M. (1987). Large sample properties of simulations using Latin hypercube sampling. *Technometrics, 29*(2), 143-151.

Taboada, M., Cabrera, E., Iglesias, M. L., Epelde, F., & Luque, E. (2011). An agent-based decision support system for hospitals emergency departments. *Procedia computer science, 4*, 1870-1879.

Takakuwa, S., & Shiozaki, H. (2004). *Functional analysis for operating emergency department of a general hospital.* Paper presented at the Simulation Conference, 2004. Proceedings of the 2004 Winter.

Taskaya-Temizel, T., & Casey, M. C. (2005). A comparative study of autoregressive neural network hybrids. *Neural Networks, 18*(5), 781-789.

Tozan, H., & Vayvay, O. (2009). Hybrid grey and ANFIS approach to bullwhip effect in supply chain networks. *WSEAS Trans. Syst, 8*(4), 461-470.

Van der Wulp, I., Van Baar, M., & Schrijvers, A. (2008). Reliability and validity of the Manchester Triage System in a general emergency department patient population in the Netherlands: results of a simulation study. *Emergency Medicine Journal, 25*(7), 431-434.

Wang, B., McKay, K., Jewer, J., & Sharma, A. (2013). *Physician shift behavior and its impact on service performances in an emergency department.* Paper presented at the Simulation Conference (WSC), 2013 Winter.

Wang, J., Li, J., Tussey, K., & Ross, K. (2012). Reducing length of stay in emergency department: A simulation study at a community hospital. *IEEE Transactions on Systems, Man, and Cybernetics-PART A: Systems and Humans, 42*(6), 1314-1322.

Wang, W.-C., Chau, K.-W., Cheng, C.-T., & Qiu, L. (2009). A comparison of performance of several artificial intelligence methods for forecasting monthly discharge time series. *Journal of hydrology, 374*(3), 294-306.

Weng, S.-J., Cheng, B.-C., Kwong, S. T., Wang, L.-M., & Chang, C.-Y. (2011). *Simulation optimization for emergency department resources allocation.* Paper presented at the Simulation Conference (WSC), Proceedings of the 2011 Winter.

Wilensky, U., & Evanston, I. (1999). NetLogo: Center for connected learning and computer-based modeling. *Northwestern University, Evanston, IL*, 49-52.

Wolfram, S. (1983). Statistical mechanics of cellular automata. *Reviews of modern physics, 55*(3), 601.

Yeh, J.-Y., & Lin, W.-S. (2007). Using simulation technique and genetic algorithm to improve the quality care of a hospital emergency department. *Expert Systems with Applications, 32*(4), 1073-1083.

Yousefi, M., & Ferreira, R. (2017). An agent-based simulation combined with group decision-making technique for improving the performance of an emergency department. *Brazilian Journal of Medical and Biological Research, 50*(5).

Yousefi, M., Yousefi, M., & Darus, A. N. (2012). A modified imperialist competitive algorithm for constrained optimization of plate-fin heat exchangers. *Proceedings of the Institution of Mechanical Engineers, Part A: Journal of Power and Energy, 226*(8), 1050-1059.

Yousefi, M., Yousefi, M., & Ferreira, R. P. M. (2015). A Review on the Application of Neural Networks for Decreasing Bullwhip Effect in Supply Chain. *International Review of Mechanical Engineering (IREME)*, 6.

Yousefi, M., Yousefi, M., Ferreira, R. P. M., & Darus, A. N. (2015). A swarm intelligent approach for multi-objective optimization of compact heat exchangers. *Proceedings of the Institution of Mechanical Engineers, Part E: Journal of Process Mechanical Engineering*, 0954408915581995.

Yousefi, M., Yousefi, M., Hooshyar, D., & de Souza Oliveira, J. A. (2015). An evolutionary approach for solving the job shop scheduling problem in a service industry. *International Journal of Advances in Intelligent Informatics, 1*(1), 1-6.

Yousefi, M., & Yusuff, R. M. (2013). Minimising earliness and tardiness penalties in single machine scheduling against common due date using imperialist competitive algorithm. *International Journal of Production Research, 51*(16), 4797-4804.

Zarandi, M. F., & Gamasaee, R. (2013). A type-2 fuzzy system model for reducing bullwhip effects in supply chains and its application in steel manufacturing. *Scientia Iranica, 20*(3), 879-899.

Zeinali, F., Mahootchi, M., & Sepehri, M. M. (2015). Resource planning in the emergency departments: A simulation-based metamodeling approach. *Simulation Modelling Practice and Theory, 53*, 123-138.

Zeng, Z., Ma, X., Hu, Y., Li, J., & Bryant, D. (2012). A simulation study to improve quality of care in the emergency department of a community hospital. *Journal of Emergency Nursing, 38*(4), 322-328.

Zhou, Z., Chan, W. K., & Chow, J. H. (2007). Agent-based simulation of electricity markets: a survey of tools. *Artificial Intelligence Review, 28*(4), 305-342.

Appendices

Appendix A

Simulation results from baseline scenario (50 replications).

No	Length-of-Stay	los-sala-amarela	los-sutura	los-pediatria	Los-Ortopedia	Los-Clinica	Los-Cirurgica
1	278.0184049	328.875	166.597398	357.8290333	140.5875	435.6666667	422.2
2	410.4238411	539.7313433	248.84739	270.9201091	196.9875	607.8333333	592.5
3	355.4457831	502.6666667	172.5503746	261.6331789	146.8369565	464	484.5
4	301.8975904	395.0694444	139.4437275	264.8957818	148.51875	287.3333333	417.2941176
5	355.8920455	428.9230769	241.545645	355.9591636	227.242623	395.2	493.3333333
6	238.0680272	184.75	200.322639	310.6093667	183.942	348.875	498.9090909
7	279.8843537	223.4545455	275.741334	317.6523	181.9557692	580	546.75
8	262.6060606	263.6029412	125.35479	321.4384923	166.2612245	429.8571429	406
9	336.4387097	349.5342466	204.489217	310.7427556	233.505	674.8	442.1666667
10	464.3170732	727.3623188	291.3611123	264.11	186.3	384.4	405.9285714
11	289.0448718	318.2222222	119.1924113	444.6652	156.4363636	534	350.2142857
12	445.191358	718.8333333	231.10758	257.5618182	166.1773585	437.8	377.125
13	480.0542169	774.3055556	195.43194	335.7445412	131.0711539	417.4	709.1666667
14	298.625	349.2121212	173.67372	308.0862105	149.1	541.5714286	465.6363636
15	234.1972789	221.2337662	201.4473038	280.6114182	204.484091	322	342
16	293.1698113	227.3870968	165.75273	456.0619467	208.674	612	525.9230769
17	252.8616352	281.6714286	168.1011515	314.6619636	144.80625	335	460.8888889
18	361.3254438	450.0793651	260.4759882	423.41635	178.712069	682.4285714	542.625
19	347.8819876	407.3529412	230.0897838	360.810275	209.3170213	430.75	503.3333333
20	371.939759	451.056338	124.7054738	473.86136	203.3480769	346.8181818	577.7142857
21	245.7852761	204.2461538	182.59263	310.11316	218.1436364	339.625	401.5833333
22	374.9090909	465.2266667	226.8328362	316.6364923	219.3461538	429.1	369.5333333
23	328.3821656	345.6805556	209.8695669	290.7392727	232.7931818	471.1666667	548.7272727
24	398.2380952	518.2272727	128.29509	412.7319	148.9404255	578.4285714	551.6956522
25	387.6363636	469.8030303	248.014305	475.6647778	194.1702128	348.3333333	532.4545455
26	263.9177215	243.8529412	134.7392475	259.0863693	186.8086957	579.1	388.3846154
27	371.7741935	435.4794521	190.4211788	437.0460267	221.2434783	506.875	383.8
28	277.372549	214.2166667	141.9062288	527.8810353	155.4893617	442	561.3846154
29	409.8095238	464.125	320.19867	404.90464	216.675	799.2727273	490.4285714
30	516.8280255	827.5774648	233.3863125	319.4930667	181.8367347	315.6666667	437
31	368.10625	514.5362319	111.33936	345.8956421	158.5565217	390.5	486.5714286
32	346.0179641	333.0294118	186.032781	408.50614	219.2651163	427.6666667	599.8823529
33	561.9731544	759.2328767	335.1942	454.5093	232.48	723.8333333	554.75
34	268.4533333	279.0149254	158.2248938	300.31708	168.675	440.6666667	506.25
35	507.6433121	701.0416667	358.569585	528.50812	198.1531915	719.8333333	417.7
36	232.3687943	185.9821429	167.0457938	299.4701818	175.86	420.375	403.6923077

37	345.2909091	476.6515152	186.562035	282.8057867	164.3333333	494.7272727	465.2857143
38	313.9683544	284.1311475	214.34787	337.512	204.3586957	643.9285714	435.1666667
39	320.0844156	391.2112676	236.40012	232.2567333	200.6660378	439	312.9
40	365.988024	478.7671233	234.71613	302.2304923	194.8924528	257.75	511.0769231
41	275.5333333	325.4117647	257.57028	289.5285867	138.6	412.6666667	451.7
42	351.7468354	431.9253731	244.9059878	390.8828	182.7	591.0909091	348.2857143
43	360.8757396	479.2794118	123.345585	322.6944	219.7830508	260.3333333	469.4615385
44	255.0540541	274.21875	100.3377375	279.1562667	182.06	390.4285714	322.4
45	249.9585799	234.4776119	280.151784	282.16552	166.2631579	363.8333333	437
46	329.9244186	343.5492958	153.64404	223.636	224.5846154	640.8181818	550.3076923
47	268.4468085	279.1267606	224.93295	189.0616	209.0131579	297.2222222	389.375
48	337.654321	382.5342466	206.16849	277.735675	210.3428571	602.9090909	347.6666667
49	335.2215569	371.3289474	217.6557075	278.8361333	230.9470588	454.5454545	557.5
50	341.9025974	449.7647059	130.54932	297.2068616	162.8470589	545.375	445.875

Appendix B:
Codes

```
% Feedforward neural network for regression
tic

clear
clc
load('Data')


m=750;
trnData = Data(1:m,:);
chkData = Data(m+1:m+201,:);

x1=trnData(:,1:19)';
t1=trnData(:,20)';


x2=chkData(:,1:19)';
t2=chkData(:,20)';

net=feedforwardnet(8);
%
%
net = train(net,x1,t1);



function out1 = feedforwardnet(varargin)
%FEEDFORWARDNET Feedforward neural network.
%
%  Two (or more) layer feedforward networks can implement any finite
%  input-output function arbitrarily well given enough hidden neurons.
%
%  <a href="matlab:doc
%  feedforwardnet">feedforwardnet</a>(hiddenSizes,trainFcn) takes a 1xN vector of N↙
hidden
%  layer sizes, and a backpropagation training function, and returns
%  a feed-forward neural network with N+1 layers.
%
%  Input, output and output layers sizes are set to 0.  These sizes will
%  automatically be configured to match particular data by <a href="matlab:doc train"↙
>train</a>. Or the
%  user can manually configure inputs and outputs with <a href="matlab:doc configure"↙
>configure</a>.
%
%  Defaults are used if <a href="matlab:doc feedforwardnet">feedforwardnet</a> is↙
called with fewer arguments.
%  The default arguments are (10,'<a href="matlab:doc trainlm">trainlm</a>').
%
%  Here a feed-forward network is used to solve a simple fitting problem:
%
%    [x,t] = <a href="matlab:doc simplefit_dataset">simplefit_dataset</a>;
%    net = <a href="matlab:doc feedforwardnet">feedforwardnet</a>(10);
%    net = <a href="matlab:doc train">train</a>(net,x,t);
%    <a href="matlab:doc view">view</a>(net)
%    y = net(x);
%    perf = <a href="matlab:doc perform">perform</a>(net,t,y)
```

```
%
%  See also FITNET, PATTERNNET, CASCADEFORWARDNET.

% Mark Beale, 2008-13-2008
% Copyright 2008-2011 The MathWorks, Inc.


%% =======================================================
%  BOILERPLATE_START
%  This code is the same for all Network Functions.

  persistent INFO;
  if isempty(INFO), INFO = get_info; end
  if (nargin > 0) && ischar(varargin{1}) ...
      && ~strcmpi(varargin{1},'hardlim') && ~strcmpi(varargin{1},'hardlims')
    code = varargin{1};
    switch code
      case 'info',
        out1 = INFO;
      case 'check_param'
        err = check_param(varargin{2});
        if ~isempty(err), nnerr.throw('Args',err); end
        out1 = err;
      case 'create'
        if nargin < 2, error(message('nnet:Args:NotEnough')); end
        param = varargin{2};
        err = nntest.param(INFO.parameters,param);
        if ~isempty(err), nnerr.throw('Args',err); end
        out1 = create_network(param);
        out1.name = INFO.name;
      otherwise,
        % Quick info field access
        try
          out1 = eval(['INFO.' code]);
        catch %#ok<CTCH>
          nnerr.throw(['Unrecognized argument: ''' code ''''])
        end
    end
  else
    [args,param] = nnparam.extract_param(varargin,INFO.defaultParam);
    [param,err] = INFO.overrideStructure(param,args);
    if ~isempty(err), nnerr.throw('Args',err,'Parameters'); end
    net = create_network(param);
    net.name = INFO.name;
    out1 = init(net);
  end
end

function v = fcnversion
  v = 7;
end

%  BOILERPLATE_END
%% =======================================================

function info = get_info
```

```
  info = nnfcnNetwork(mfilename,'Feed-Forward Neural Network',fcnversion, ...
    [ ...
    nnetParamInfo('hiddenSizes','Hidden Layer Sizes','nntype.strict_pos_int_row',↙
10,...
    'Sizes of 0 or more hidden layers.'), ...
    nnetParamInfo('trainFcn','Training Function','nntype.training_fcn','trainlm',...
    'Function to train the network.'), ...
    ]);

  % TODO - hiddenSizes => hiddenSizes
end

function err = check_param(param)
  err = '';
end

function net = create_network(param)

  % Layers
  net = network;
  Nl = length(param.hiddenSizes)+1;
  net.numLayers = Nl;
  net.biasConnect = true(Nl,1);
  [j,i] = meshgrid(1:Nl,1:Nl);
  net.layerConnect = (j == (i-1));
  for i=1:Nl
    if i == Nl
      net.layers{i}.name = 'Output';
    else
      if (Nl == 2)
        net.layers{i}.name = 'Hidden';
      else
        net.layers{i}.name = ['Hidden ' num2str(i)];
      end
      net.layers{i}.size = param.hiddenSizes(i);
      net.layers{i}.transferFcn = 'tansig';
    end
    net.layers{i}.initFcn = 'initnw';
  end

  % Inputs
  net.numInputs = 1;
  net.inputConnect(1,1) = true;
  net.inputs{1}.processFcns = {'removeconstantrows','mapminmax'};

  % Outputs
  net.outputConnect(Nl) = true;
  net.outputs{Nl}.processFcns = {'removeconstantrows','mapminmax'};

  % Training
  net.dividefcn = 'dividerand';
  net.trainFcn = param.trainFcn;
  net.performFcn = 'mse';

  % Adaption
  net.adaptFcn = 'adaptwb';
```

```
  net.inputWeights{1,1}.learnFcn = 'learngdm';
  net.layerWeights{find(net.layerConnect)'}.learnFcn = 'learngdm';
  net.biases{:}.learnFcn = 'learngdm';

  % Plots
  net.plotFcns = {'plotperform','plottrainstate','ploterrhist','plotregression'};
end
```

```
% Recurrent neural netwrook for regression
tic

clear
clc
load('Data')

m=750;
trnData = Data(1:m,:);
chkData = Data(m+1:m+201,:);

x1=trnData(:,1:19)';
t1=trnData(:,20)';


x2=chkData(:,1:19)';
t2=chkData(:,20)';

%
% Recurent neural network

net = layrecnet(1:2,8);
view(net)
net = train(net,x1,t1);




RNN_output=net(x2);

RMSE_Rnn = mean((t2 - RNN_output).^2)^0.5

mean(abs(t2- RNN_output)./t2)*100


%
%
% %

function out1 = layrecnet(varargin)
%LAYRECNET Layered recurrent neural network.
%
%  Layer recurrent networks with two (or more) layers can learn to
%  predict any dynamic output from past inputs given enough hidden
%  neurons and enough recurrent layer delays.
%
%  <a href="matlab:doc layrecnet">layrecnet</a>(layerDelays,hiddenSizes,trainFcn)↙
takes a row vectors
%  of layers delays, a row vector of hidden layer sizes, and a
%  backpropagation training function, and returns a layer recurrent neural
%  network with N+1 layers.
%
%  Input, output and output layers sizes are set to 0.  These sizes will
%  automatically be configured to match particular data by <a href="matlab:doc train"↙
>train</a>. Or the
%  user can manually configure inputs and outputs with <a href="matlab:doc configure"↙
```

```
>configure</a>.
%
%  Defaults are used if <a href="matlab:doc layrecnet">layrecnet</a> is called with
fewer arguments.
%  The default arguments are (1:2,10,'<a href="matlab:doc trainlm">trainlm</a>').
%
%  Here a layer recurrent network is used to solve a time series problem.
%
%    [X,T] = <a href="matlab:doc simpleseries_dataset">simpleseries_dataset</a>;
%    net = <a href="matlab:doc layrecnet">layrecnet</a>(1:2,10);
%    [Xs,Xi,Ai,Ts] = <a href="matlab:doc preparets">preparets</a>(net,X,T);
%    net = <a href="matlab:doc train">train</a>(net,Xs,Ts,Xi,Ai);
%    <a href="matlab:doc view">view</a>(net);
%    Y = net(Xs,Xi,Ai);
%    perf = <a href="matlab:doc perform">perform</a>(net,Y,Ts)
%
%  To predict the next output a step ahead of when it will occur:
%
%    net = <a href="matlab:doc removedelay">removedelay</a>(net);
%    [Xs,Xi,Ai,Ts] = <a href="matlab:doc preparets">preparets</a>(net,X,T);
%    Y = net(Xs,Xi,Ai);
%
%  See also NARXNET, TIMEDELAYNET, DISTDELAYNET.

% Mark Beale, 2008-13-2008
% Copyright 2008-2011 The MathWorks, Inc.

%% =======================================================
%  BOILERPLATE_START
%  This code is the same for all Network Functions.

  persistent INFO;
  if isempty(INFO), INFO = get_info; end
  if (nargin > 0) && ischar(varargin{1}) ...
      && ~strcmpi(varargin{1},'hardlim') && ~strcmpi(varargin{1},'hardlims')
    code = varargin{1};
    switch code
      case 'info',
        out1 = INFO;
      case 'check_param'
        err = check_param(varargin{2});
        if ~isempty(err), nnerr.throw('Args',err); end
        out1 = err;
      case 'create'
        if nargin < 2, error(message('nnet:Args:NotEnough')); end
        param = varargin{2};
        err = nntest.param(INFO.parameters,param);
        if ~isempty(err), nnerr.throw('Args',err); end
        out1 = create_network(param);
        out1.name = INFO.name;
      otherwise,
        % Quick info field access
        try
          out1 = eval(['INFO.' code]);
        catch %#ok<CTCH>
          nnerr.throw(['Unrecognized argument: ''' code ''''])
```

```
        end
      end
    else
      [args,param] = nnparam.extract_param(varargin,INFO.defaultParam);
      [param,err] = INFO.overrideStructure(param,args);
      if ~isempty(err), nnerr.throw('Args',err,'Parameters'); end
      net = create_network(param);
      net.name = INFO.name;
      out1 = init(net);
    end
end

function v = fcnversion
  v = 7;
end

%  BOILERPLATE_END
%% =========================================================

function info = get_info
  info = nnfcnNetwork(mfilename,'Layer Recurrent Neural Network',fcnversion, ...
    [ ...
    nnetParamInfo('layerDelays','Layer Delays','nntype.strictpos_delayvec',1:2,...
    'Row vector delays in each layers feedback connection.'), ...
    nnetParamInfo('hiddenSizes','Hidden Layer Sizes','nntype.strict_pos_int_row',↙
10,...
    'Sizes of 0 or more hidden layers.'), ...
    nnetParamInfo('trainFcn','Training Function','nntype.training_fcn','trainlm',...
    'Function to train the network.'), ...
    ]);
end

function err = check_param(param)
  err = '';
end

function net = create_network(param)
  net = feedforwardnet(param.hiddenSizes,param.trainFcn);
  for i=1:(net.numLayers-1)
    net.layerConnect(i,i) = true;
    net.layerWeights{i,i}.delays = param.layerDelays;
  end
  net.plotFcns = [net.plotFcns {'plotresponse','ploterrcorr','plotinerrcorr'}];
end
```

```
% ANFIS regression

tic

clear
clc
load('Data')


m=750;

trnData = Data(1:m,:);
chkData = Data(m+1:m+201,:);

% To start the taining, you need a FIS structure that
% specifies the structure and initial parameters of the
% FIS for learning. The genfis1 function handles this specification.

fismat = genfis1(trnData);

% Start the training.

[fismat1,error1,ss,fismat2,error2] = ...
      anfis(trnData,fismat,[],[0 0 0 0],chkData);


  % Because the checking data option of anfis is invoked, the final FIS you choose is
  % the one associated with the minimum checking error. This result is stored in
fismat2.
  % Plots these new membership functions.

%  training
anfis_output = evalfis([trnData(:,1:19); chkData(:,20)],fismat2);


MSE_anfis = mean((chkData(:,1:19) - anfis_output).^2)

function [output,IRR,ORR,ARR] = evalfis(input, fis, numofpoints);
%



ni = nargin;
if ni<2
   disp('Need at least two inputs');
   output=[];
   IRR=[];
   ORR=[];
   ARR=[];
   return
end

% Check inputs
if ~isfis(fis)
   error('The second argument must be a FIS structure.')
elseif strcmpi(fis.type,'sugeno') & ~strcmpi(fis.impMethod,'prod')
   warning('Fuzzy:evalfis:ImplicationMethod','Implication method should be "prod" for
```

```
Sugeno systems.')
end
[M,N] = size(input);
Nin = length(fis.input);
if M==1 & N==1,
   input = input(:,ones(1,Nin));
elseif M==Nin & N~=Nin,
   input = input.';
elseif N~=Nin
   error(sprintf('%s\n%s',...
      'The first argument should have as many columns as input variables and',...
      'as many rows as independent sets of input values.'))
end

% Check the fis for empty values
checkfis(fis);

% Issue warning if inputs out of range
inRange = getfis(fis,'inRange');
InputMin = min(input,[],1);
InputMax = max(input,[],1);
if any(InputMin(:)<inRange(:,1)) | any(InputMax(:)>inRange(:,2))
   warning('Fuzzy:evalfis:InputOutOfRange','Some input values are outside of the
specified input range.')
end

% Compute output
if ni==2
   numofpoints = 101;
end

[output,IRR,ORR,ARR] = evalfismex(input, fis, numofpoints);
```