T.R.
TURKISH NAVAL ACADEMY
NAVAL SCIENCE AND ENGINEERING INSTITUTE
DEPARTMENT OF OPERATIONS RESEARCH

A MULTI-OBJECTIVE OPTIMIZATION MODEL FOR LOCATING SEARCH AND RESCUE BOATS

A Master Thesis

Nasuh RAZI

Advisor: Asst. Prof. Dr. Mümtaz KARATAŞ

İstanbul, 2016

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ARAMA KURTARMA BOTLARININ YERLEŞİMİ İÇİN ÇOK AMAÇLI BİR ENİYİLEME MODELİ

Nasuh RAZI

DENİZ HAREKAT ANALİZİ YÜKSEK LİSANS PROGRAMI

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Sınav Tarihi : 31 Mayıs 2016

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ACKNOWLEDGEMENT

I would like to express my deep appreciation to everyone involving and supporting on preparing this thesis.

I owe a debt of gratitude to my wife Senem, my son Rüzgar and my family. Their love, support and patience were the biggest motivation of this thesis.

It was a chance and honor to be supervised by Asst. Prof. Dr. Mümtaz KARATAŞ during this thesis. I would like to acknowledge my deep appreciation for his lead and motivation that ensured our efforts to transform into valuable results.

I wish to express my deep sense of gratitude to Assoc. Prof. Dr. Hakan TOZAN, Asst. Prof. Dr. M.Murat GÜNAL, Asst. Prof. Dr. Ertan YAKICI and Asst. Prof. Dr. Kerim GÖZTEPE for their lectures and insights that expanded my horizon.

I would like to thank to my committee member Prof. Dr. Özalp VAYVAY for his comments and contributions.

It was reassuring to feel endless support of Dr. Mustafa KARADENİZ.

Finally, it was a pleasure to have sincere fellowship of my colleague Evren YILMAZ.

DEDICATION

Değerli eşim ve canım oğluma

DISCLAIMER STATEMENT

The views expressed in this thesis are those of the author and do not reflect the official policy or position of the Turkish Naval Forces, Turkish Naval Academy and Naval Science and Engineering Institute. I declare that all materials in this thesis are used according to rules and ethics.

ÖZET

ARAMA KURTARMA BOTLARININ YERLEŞİMİ İÇİN ÇOK AMAÇLI BİR ENİYİLEME MODELİ

Nasuh RAZI

Harekat Analizi Yüksek Lisans Tezi, 2016

Danışman: Yrd.Doç.Dr. Mümtaz KARATAŞ

Anahtar Kelimeler: Tam Sayılı Programlama, Kaynak Yerleşimi, AHP, *K*-Ortalama Kümeleme, Eniyileme, Kesikli Olay Benzetimi, Arama Kurtarma.

Deniz Arama Kurtarma (SAR) faaliyetleri, denizde oluşan tehlike ve kaza durumunda can kaybı, yaralanma ve maddi hasarı en aza indirmeyi hedefleyen önemli bir süreçtir. Kazalara ne kadar hızlı müdahale edilirse can kayıpları, yaralanmalar ve maddi hasar da o denli azaltılabilir. Dolayısıyla SAR kaynaklarının en iyi şekilde konuşlandırılması, hızlı müdahale için mükemmel bir planlama ile ortaya konan stratejik bir yöntemdir. Bu tez çalışmasındaki temel hedefimiz, eniyileme ve benzetim temelli bir yöntem kullanarak SAR kaynaklarının en etkin şekilde nasıl konuşlandırılması gerektiğini ortaya koymaktır. Kullandığımız yöntem iki aşamalıdır: ilk aşamada, çok amaçlı bir model olan Kaza Bazlı Bot Konuşlandırma Modeli kullanılarak SAR kaynaklarının en iyi yerleşim

planı oluşturulmuştur. İkinci aşamada ise, analitik çözümün vermiş olduğu yerleşim planının stokastik talep karşısındaki performansını test etmek için kesikli olay benzetim modeli kullanılmıştır.

Geliştirilen yöntem, çevre denizlerimizde en yüksek trafik yoğunluğuna ve kaza riskine sahip Ege Denizi üzerinde uyguladık. Bu uygulamadaki amaç, kazalara müdahalede toplam gecikme süresini ve planlı bütçe aşımını, botlar arasındaki iş yükünün dengeli dağılımı ile en aza indirmektir.

ABSTRACT

A MULTI-OBJECTIVE OPTIMIZATION MODEL FOR LOCATING SEARCH AND RESCUE BOATS

Nasuh RAZI

Operations Research, Master of Science Thesis, 2016

Advisor: Asst.Prof. Dr. Mümtaz KARATAŞ

Key Words: Integer Programming, Facility Location, AHP, K-Means Clustering, Optimization, Discrete Event Simulation, Search and Rescue.

Maritime Search and Rescue (SAR) operation is a critical process which aims to minimize the loss of life, injury and material damage by rendering aid to persons in distress or imminent danger at sea. Fatalities, injuries and damage can be reduced if incidents are responded as quickly as possible. Thus, optimal allocation of SAR resources is a strategic process which is to be carried out with an excellent planning to react rapidly. In this thesis, our main goal is to determine optimal allocation of SAR resources with an optimization and simulation based methodology. Our methodology works in two stages; we first determine an optimal allocation scheme of SAR resources with a multi-objective model, the Incident-Based Boat Allocation Model (IB-BAM). Next, we use discrete event simulation to test the performance of our analytical solution under stochastic demand. With the heaviest traffic and maritime risk, we applied our methodology to allocate SAR resources optimally in the Aegean Sea, as a case study in terms of minimizing total weighted delay, exceedance on budget and total deviation of supply from capacity.

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ABBREVIATIONS

AHP : Analytic Hierarchy Process
DES : Discrete Event Simulation
IB-BAM : Incident-Based Boat Allocation Model
***K*-MCA** : *K*-Means Clustering Algorithm
MCLP : Maximal Covering Location Problem
MCDM : Multi Criteria Decision Making
MIP : Mixed Integer Programming
***P*-CP** : *P*-Center Problem
***P*-MP** : *P*-Median Problem
SAR : Search and Rescue
SCP : Set Covering Problem
TURCG : Turkish Coast Guard
***WK*-MCA** : Weighted *K*-Means Clustering Algorithm
ZDM : Zonal Distribution Model

1 INTRODUCTION

1.1 OVERVIEW

Each year, Search and Rescue (SAR) organizations receive thousands of distress signals and calls from the vessels in danger. As the difference between life and death can sometimes be measured in minutes, quick response to these signals plays a vital role to reduce fatalities and damage. However, a SAR operation consumes considerable amounts of time, effort and money as well. Thus, emergency response actions should be well-planned and neatly organized. SAR operation planning can be counted as an emergency system planning.

Green and Colesar (2004)'s survey on emergency response systems in OR/MS literature states that despite their various challenges, OR/MS application is an important way in minimizing the impact of unexpected emergencies. In addition to such application fields as fire-fighting, emergency medical services and sensor networks, this observation is particularly applicable to SAR organizations. The way SAR organizations are established is generally decided by political and local factors. Thus, we propose an analytic approach to plan an optimum SAR organization.

1.2 OBJECTIVES

The main goal of this thesis is to establish an optimization model for allocating SAR resources optimally in terms of multiple objectives. We develop a multi-objective Incident-Based Boat Allocation Model (IB-BAM) comprised of the common facility location approach, *p*-median problems (*p*-MP), with a number of contributions such as technical and business rules. Using historical incident data, IB-BAM provides an optimal solution according to constructed factors. Since our optimization model uses deterministic incident data, we test its performance with a simulation model which incorporates stochastic incident data. Technically, response to incidents by SAR resources in responsible region could be conceptualized as a queuing system, of which elements are incidents-customers, and resources-multiple servers. At this

point, we develop a discrete-event simulation (DES) model to evaluate the efficiency of the optimization model in cases of uncertainty.

We demonstrated the performance of our optimization model for the SAR boat allocation problem in the Aegean Sea, the western sea region of Turkey. Our main ambition is to allocate SAR boats among ports in the Aegean Sea with the objectives of minimizing total weighted delay, exceedance on budget and total deviation of supply from capacity.

1.3 THESIS ORGANIZATION

The thesis is organized as follows. Chapter One is the introduction chapter which includes an overview of the thesis, objectives, and organization. Chapter Two is composed of literature review of facility location methodologies, DES and other related concepts with our methodology. In Chapter Three we describe our methodology for the optimization and simulation models. Chapter Four is the case study of allocating SAR resources among ports in the Aegean Sea. In Chapter Five, we discuss our results. Finally, Chapter Six includes the conclusions of the thesis and further remarks.

2 LITERATURE REVIEW

This chapter includes a summary of related literature on facility location problems and DES. We also include literature on the two techniques, AHP and *k*-means clustering, that we used in our methodology.

2.1 FACILITY LOCATION PROBLEMS

Location theory has emanated from Pierre de Fermat, Evagelistica Torricelli (a student of Galileo), and Battista Cavallieri who stated the basic Euclidean spatial median problem early in the seventeenth century; but the study of Alfred Weber (1909) which was about locating a single warehouse with the objective of minimizing distances between it and customers is accepted as the origin of location science (Owen and Daskin, 1998, p.423-427).

Allocation of facilities is a strategic process and most popularly seen in private and public firms. Deployment of a new construction is generally costly and requires take a number of factors into consideration such as distances, customer types and locations, long term relocation plans. It is of high importance to conduct an analytic work due to the remarkable cost of changing decisions on facility locations. Facility location problem is utilized in various sectors. Along with the allocation of warehouses for a supply chain in private firms, those of emergency response systems, such as fire-fighting, ambulance and SAR operations in public sector, are the main application areas of facility problem. Facility location problems have been formulated with a number of different objectives such as (Farahani et al., 2010, p.1689-1709);

- Minimizing total/fixed/setup/operating cost.
- Minimizing the longest distance from activated facilities.
- Minimizing average time/distance traveled.
- Minimizing maximum time/distance traveled.
- Minimizing total time/distance traveled.
- Minimizing total number of facilities activated.
- Maximizing service level/coverage.
- Maximizing responsiveness.

With these objectives, a considerable amount of studies, of which *p*-median problems (*p*-MP), *p*-center problems (*p*-CP), and covering problems that can be sub-categorized as the maximal covering location problems (MCLP) and set-covering problems (SCP) constitute the majority, have been held to deal with this challenge.

There is no doubt to say that distance is in inverse proportion to accessibility for a facility location. As traveled distance increases, accessibility and effective of a facility definitely decreases. Thus, traveled distance is a significant factor to measure facility's effectiveness. The *p*-MP, first introduced by (Hakimi, 1964, p.450-459), seeks the location of *p* facilities with the objective of minimizing the total weighted distances traveled between demands and facilities (Church and ReVelle, 1976, p.406-415, Church et al., 2004, p.491-502). The *p*-CP, also known as the *minimax* problem, is to locate *p* facilities with the objective of minimizing the maximum distance of any demand to its closest facility (Drezner, 1984, p.351-361, Suzuki and Drezner, 1996, p.69-82, Davidović et al., 2011, p.1367-1376).

Besides traveled distance, coverage is another common measure of effectiveness for a facility in a location problem. In literature, coverage is firstly utilized as an objective by Toregas et al. (1971, p.373-377). A distinguished review by Farahani et al. (2010, p.1689-1709) states that decision makers define coverage factor as distance, population coverage and pre-determined time threshold. In other words, the demand is said to be covered if it can be served within a specified time or distance. In the SCP, the objective is to minimize the cost of facility location while satisfying all demand points. Such problems also allow us to analyze the minimum number of facilities required to achieve the goal (Beasley and Jørnsten, 1992, p.293-300; Badri et al., 1998, p.243-260; Caprara et al., 2000, p.353-371). In cases where resources are not sufficient to satisfy all demand, the objective is shifted so as to give the desired level of coverage to as many customers as possible with available resources. This new objective is that of the MCLP (Church and ReVelle, 1974, p.406-415; Schilling et al., 1993, p.25-55; Balcik and Beamon, 2008, p.101-121)**,** and it finds application in other areas as well, such as communication network design (Craparo et al., 2011, p.560-572).

Studies such as Francis and White (1974), Tansel et al. (1983, p.482-497), Daskin (1997, p.763), Krumke (1995, p.67-71), Brotcorne et al. (2003, p.451-463), Hale and Moberg (2003, p.21-35), Shen et al. (2003, p.40-55), Drezner (2004, p.899-912),

Li et al. (2011, p.281-310), Murali et al. (2012, p.78-87) are fine examples for the readers who are interested in learning more about facility location problems.

Classical facility location problems comprise of four main items: (1) demands/customers, (2) facilities, (3) a space in which demands and facilities are located and (4) a metric to indicate distance and time in system (ReVelle and Eiselt, 2005, p.1-19). As decision makers formulate their problem with these items in different forms, facility location problem has various types of sub-classes, of which security-military firms, safety organizations and emergency response systems constitute a large amount. Monitoring an area of interest by well-established sensor network is a considerable activity in support of security with many useful functions such as tracking, detection, recognition, early warning and analysis continuously. Erdem and Sclaroff (2004) seek the optimal placement of static cameras in a floor plan while minimizing total number of cameras required. Murray et al. (2007, p.133-147) develop a MCLP model to locate video sensor placement in an urban area. In their study, they develop a methodology that combines GIS-based optimization approach and visibility analysis with the aim of covering as much area as possible in 3D. Sensor networks are also used as early warning systems in security firms. Berry et al. (2006, p.218-224) study the problem of sensor allocation in municipal water networks with a *p*-MP MIP model for minimizing the impact of a possible contamination. They utilize the model for intercepting emergency cases such as accidental contamination or chemical terrorist attacks that threats the public health on municipal water networks as quickly as possible. Beside the water network system, municipal and agricultural waste management is also another public firm that the facility location theory is used to be conducted. In their study, Dantrakul et al. (2014, p.3596-3604) construct three different methods, considering median and center model, to allocate waste management system facilities and experiment methods in Chiang Mai city and 5 provinces of Northern Thailand. In another example, Bautista and Pereira (2006, p.617-629) address the problem of locating collection points of waste management in a metropolitan area. They formulate the problem as SCP with maximum satisfiability problem (MAX-SAT) techniques and experiment in waste management system of Barcelona.

Fire-stations, ambulances and emergency medical services (EMS) are main emergency response systems that placed to serve clients in a short response time.

Badri et al. (1998, p.243-260) formulate an integer goal programming model, considering SCP, with 11 strategic objectives to locate fire-station in Dubai City. Serra and Marianov (1998, p.383-394) take the similar problem with uncertain demand, travel time or distance and develop a *p*-MP model to allocate fire stations in Barcelona. Similarly, Aktaş et al. (2013, p.240-255) address the same problem for Istanbul Metropolitan Municipality with SCP and MCLP models. However, they seek the locations of fire-stations with the aim of serving clients within a five-minute response time and improve the level of coverage. In another, Chevalier et al. (2012, p.173-182) develops a decision-support system for allocating fire stations in Belguim. They take real cases such as queuing and staff problem into consideration and model the problem as a MIP.

It is clear that quick response to accidents plays a crucial role for a victim to survive. Adenso-Diaz and Rodriguez (1997, p.181-187) seek the locations of ambulance bases where satisfy a desired coverage level in Leon, Spain. They formulate the problem with MCLP and solve it with Tabu Search heuristic method. Erdemir et al. (2008a, p.610-632) develop two detached models as quadratic MCLP and geometrical network forms to serve stationary demand points and continuous paths from facilities. In another paper of theirs (Erdemir et al., 2008b, p.1105-1114), they address the problem of locating aeromedical bases optimally to respond motor vehicle crashes which has a tendency for trauma injuries. They apply their quadratic MCLP model to maximize total coverage of interested area in New Mexico. Jia et al. (2007, p.41-55) apply three traditional facility location approaches, covering, center and median models, to allocate medical supply storages where contains vaccines, antibiotics, drugs and medical equipment to develop under a possible chemical, biological, radiological and nuclear(CBRN) terrorist attack in LA. Lee et al. (2009, p.476-490) design a decision support tool to determine optimal locations for point-of-dispensing (POD) where deals with unexpected large-scale medical concerns.

In literature, we confronted with a number of military applications of facility location problem. Dawson et al. (2007, p.5-17) develop a hybrid technique which combines two traditional methods, *p*-median and *p*-center, to locate security teams for security of US Air Force Intercontinental Ballistic Missile Systems (ICBM) while Overholts et al. (2009, p.838-852) utilize two-stage MCLP model to improve scheduled

maintenance activities of ICBM within a desired security level. Sathe and Miller-Hooks (2005, p.127-136) try to locate guarding forces such as military and police units for covering as much facilities as possible in a probabilistic network with minimum cost. Operational support hubs are strategic locations where improve operability and effectiveness of a military logistic system. Ghanmi (2011, p.638-650) develops a discrete facility location model to determine hub location with optimizing aircraft routes. He formulates the model with a mixed integer nonlinear programming and experiments for the Canadian Forces with historical data. Sarikaya (2009) seeks the optimal allocation of orbit locations for Turkish Airborne Early Warning and Control (AEW&C) aircrafts to cover all responsibility regions. He generates a MCLP model and tests it with three different combat scenarios. Ebelan (2004) utilizes three traditional methods, SCP, *p*-MP and *p*-CP, to allocate strip alert sites where host air defense units for intercepting threats in the Contiguous United States (CONUS) immediately. Similarly, Alkanat (2008) applies both SCP and MCLP models to optimally locate SAM sites to defend Turkish Air Space. In addition to these studies about air assets, allocation of SAR aircrafts is another extensive military field that facility location problem has been applied. Basdemir (2000) studies the problem of allocating TUAF SAR helicopters to cover demand points in area of interest. He formulates the problem with a MCLP model and solves for the Aegean and the Western Mediterranean regions of Turkey with three different scenarios about coverage ranges. Afshartous et al. (2009, p.1086-1096) propose an optimization and simulation methodology to determine optimal allocation of United States Coast Guard (USCG) air stations. They formulate and solve the problem as an Uncapacitated Facility Location Problem (*p*-UFLP), a hybrid of *p*-MP and UFLP. Then, they evaluate the results of optimization model with simulation. The authors assumed that the demand for each client is equal and served with a single resource. Although we consider it a similar problem, our structure differs in that demand for each incident varies and each demand can be covered by supplies from multiple resources (boats). Similarly, Nelson et al. (2014, p.2761) develop an optimization model to locate USCG aircrafts with the aim of improving fleet operational performance. As they seek the optimal allocation and aircraft deployment, they take SAR and scheduled missions into consideration together. For another example, Acar (2015) applies SCP, MCLP and *p*-MP models to deploy TUAF SAR resources.

He utilizes each model for different objectives: SCP to find minimum number of SAR Deployment Points (DPs) required for covering all training areas, MCLP to cover as much area as possible with a given SAR DP number and *p*-MP to allocate SAR DPs with the objective of minimizing aggregate or average response time. As we narrow the scope of our review to SAR allocation problems, a number of studies that consider search theory were seen in literature. Abi-Zeid and Frost (2005, p.630-653) design a geographic decision support tool that applies search theory to determine optimal search plan for the Canadian Forces in case of missing aircrafts while Wysokiński et al. (2014, p.776-785) develop a similar system that regards missing person's behavior for the Polish SAR teams. Breivik and Allen (2008, p.99-113) present a stochastic trajectory model which concerns motions of drifting objects and use the model for the Norwegian Sea and the North Sea. Although above-mentioned tools and systems support SAR operations in terms of maximizing detection probability of missing objects, these are not appropriate for allocation of SAR resources.

However, studies (Losea, 1976; Azofra et al., 2007, p.941-951; Radovilsky and Koermer, 2007, p.130-135; Wagner and Radovilsky, 2012, p.1035-1049; Venäläinen, 2014; Ai et al., 2015, p.170-188; Pelot et al., 2015, p.369-402) deal with the problem of optimal allocation of CG boats. Losea (1976) approaches to the problem of allocating USCG units from social and political view without any attempt for constructing a model. As a general method for allocating SAR units, Azofra et al. (2007, p.941-951) formalize two gravitational models, Individual Distribution Model and Zonal Distribution Model (ZDM), to determine optimum locations of SAR boats. In the first one, they evaluate each location individually with several factors and give a coefficient to each of them for discriminating in step of assignment. In the Zonal Distribution Model (ZDM), accidents are clustered into zones and each zone is representing with a centroid called "*superaccident*" which is the arithmetic mean of the latitudes and longitudes of the accidents that occurred in the zone. Then, the effectiveness of all possible allocation plans is computed with respect to the distance between each port and superaccident, and superaccident weights. Radovilsky and Koermer (2007, p.130-135) develop an ILP model to allocate SAR boats into USCG stations. In their model, they aim to minimize capacity deviation at the station while assigning a boat to multiple demand points is not allowed. In addition, they define

boats as variables and do not take operation capacities into consideration. In their study, Wagner and Radovilsky (2012, p.1035-1049) improve Radovilsky and Koermer (2007, p.130-135)'s work and develop a decision support tool with Multi-Objective Mixed Integer Problem(mo-MIP) model, namely the Boat Allocation Tool (BAT). They try to minimize three objectives such as the deviation on supply from demand, number of boats types at a station and total cost. Most importantly, they provide considerable improvement on USCG fleet performance. Venäläinen (2014) utilizes GIS methods with wind and wave impacts on navigation to evaluate emergency response in the Gulf of Finland. In their study, Ai et al. (2015, p.170-188) develop an integrated nonlinear optimization model which deals with location, allocation and configuration of maritime emergency response bases and vessels. In addition, they generate a hybrid heuristic and genetic algorithm to solve the problem. Pelot et al. (2015, p.369-402) study the problem of locating SAR boats of the Canadian Coast Guard (CCG). In their study, they try to deploy different types of SAR boats with respect to historical incident data which comprises of different incident types.

2.2 ANALYTIC HIERARCHY PROCESS (AHP)

The AHP technique, stated firstly by (Saaty, 1980), is a prevalent technique to deal with discrete alternative problems in terms of multiple criteria (Steuer and Na, 2003, p.496-515). It helps researchers to decompose the problem into hierarchical structure for considering relation of alternatives with respect to criteria (Daim et al., 2009, p.232-243). The adaptability of the AHP technique makes it used in various problems. While being utilized in solving problems, the technique can also be used in determining relative weights/priorities of existing alternatives.

AHP methodology has four main steps to follow (Saaty, 2008, p.83-98; Goossens and Basten, 2015, p.31-41):

(1) Define the problem and state desired objectives.

(2) Construct the decision hierarchy tree. The top of the tree is the goal of the decision-maker. The intermediate level comprises of criteria and sub-criteria that relate to objective while the lowest level is about alternatives.

(3) Determine priorities of criteria and alternatives by pairwise comparison.

Firstly, compare each criterion with others in same level to obtain the weights of them. Then, compare each alternative with others according to each criterion in upper level. In each comparison, calculate a Consistency Ratio (CR) to measure how consistent the judgments have been. If the CR is greater than 0.1, then the judgments are considered to be untrustworthy and must be repeated.

(4) Weigh the priorities in the level immediately below by using the priorities obtained from comparisons, for every element. Then add its weighed values for each element in the level below and obtain its overall or global priority. Continue this process of weighing and adding until the final priorities of the alternatives are obtained.

In pairwise comparison step, decision-makers utilize the intensity matrix (Table 2.1) which is developed by Saaty (1987, p.161-176). The scale indicates the relative importance or dominance between each alternative. While higher values indicate that selected alternative is more important than its compared one, scale "1" means that compared items have equal importance.

Table 2.1 Intensity Table Used in Pairwise Comparisons (Saaty, 1987).

Intensity of Importance	Definition	Explanation
1	Equal importance	Two activities contribute equally to the objective
3	Moderate importance	Experience and judgment slightly favor one activity over another
5	Strong importance	Experience and judgment strongly favor one activity over another
7	Very strong or demonstrated importance	An activity is favored very strongly over another; its dominance demonstrated in practice
9	Extreme importance	The evidence favoring one activity over another is of the highest possible order of affirmation
2,4,6,8	Intermediate values between the two adjacent judgments	When compromise is needed
Reciprocals of above nonzero	If activity *i* has one of the above nonzero numbers assigned to it when compared with activity *j*, then *j* has the reciprocal value when compared with *i*.	

A comprehensive review of Vaidya and Kumar (2006, p.1-29) analyzes the applications of the AHP in literature with ten themes such as selection, evaluation, benefit–cost analysis, allocations, planning and development, priority and ranking, and decision-making. In addition, they also categorize all studies in terms of application area, such as manufacturing, engineering, personal, social, political, education, industry, government, and others. Korpela and Tuominen (1996, p.169-180) develop an approach to select warehouse sites by the AHP while both tangible and intangible criteria are considered. Similarly, Lirn et al. (2004, p.70-91) utilize the AHP technique to the problem of transshipment port selection. Amer and Daim (2011, p.420-435) overcome the problem of selecting renewable energy option for Pakistan with the AHP. They evaluate four alternative renewable energy options such as wind energy, solar photovoltaic, solar thermal and biomass energy with five criteria and 22 sub-criteria. Karacan (2015) develops a hybrid decision support tool that considers the AHP with other MCDM techniques such as TOPSIS/Fuzzy TOPSIS, VIKOR/Fuzzy VIKOR, and Goal Programming. The author tests the tool in selection of obesity surgery selection among three alternatives. Işıklar and Büyükozan (2007, p.265-274) study the problem of mobile phone selection by utilizing AHP methodology. Sivilevičius and Maskeliūnaite (2010, p.368-381) try to increase the quality of railway transportation and for that purpose, they get passengers evaluated a number of criteria which are categorized mainly into four groups and conduct the AHP technique. Recent studies of Ho (2008, p.211-228), Dağdeviren et al. (2009, p.8143-8151), Amiri (2010, p.6218-6224), Ishizaka et al. (2011, p.1801-1812), Stein (2013, p.157-171), Herva and Roca (2013, p.77-84), Ren and Sovacool (2014, p.589-597), Luthra et al. (2015, p.762-776) provide further AHP applications for interested researchers.

2.3 *K*-MEANS CLUSTERING

In a facility location problem, locations constitute the majority of inputs in a model. However, as amount of location data increases, it makes the optimization model so complex to solve in a decent time. In addition, using large-sized data brings out a number of issues by which the decision-maker must confront such as data collection cost, modeling cost, computing cost, confidentiality concerns and statistical data uncertainty (Francis et al., 2009, p.171-208). Thus, data aggregation that Fredrikson

et al. (1999, p.26.34) state also as "*a single point that represents or summarizes the group of data points*" is a practicable method to deal with these hardships.

In literature, researchers encounter with a number of clustering techniques. With a more than 50 years history, *k*-means clustering algorithm (*k*-MCA) is prevalent method for data clustering due to its simplicity, efficiency and implementation with ease (Jain, 2010, p.651-666). The algorithm provides *k* centers, called "*centroids*", on given *n* data while minimizing the squared error between the center of cluster and each point in it (see Figure 2.1). In application process, *k*-MCA follows three main steps (Jain and Dubes, 1988):

(1) Initial partition with *k*-cluster,

(2) Assigning new patterns to nearest cluster for generating a new partition,

(3) Determining new centroids. Re-apply step 2 and step 3 until obtaining stable clusters.

Main parameter of *k*-MCA, *k*-number of clusters to be generated, can be determined in various ways. While Tibshirani et al. (2001, p.411-423) develop a heuristic method, the gap statistic, Kodinariya and Makwana (2013, p.90-95) mention six approaches: rule of thumb, elbow method, information criterion approach, information theoretic approach, choosing *k* using the Silhouette and cross-validation in their review. The algorithm runs separately for any *k* value no matter which method is used for determining "*k*" (Jain, 2010, p.651-666).

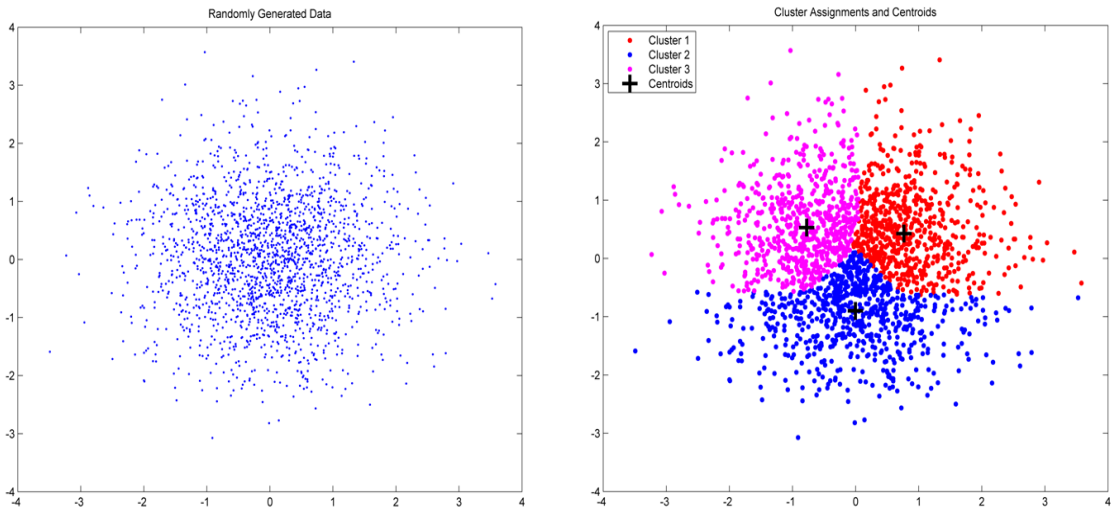

Figure 2.1 (a) Randomly generated data, (b) 3-means cluster and centroids.

Data aggregation has been applied for a number of purposes such as grouping, defining patterns and determining similarity of data. There are a number of papers that contain data aggregation for different purposes in facility location models. Nemes et al. (2004, p.15-20) study the problem of evaluating the performance of AIDS care clinics where deliver antiretroviral treatment in Brasil. They conduct a questionnaire at 27 sites to determine service quality and utilize *k*-means clustering to gather health services in four groups as "Best", "Medium", "Poor" and "Very Poor" in terms of questionnaire scores. Liao and Guo (2008, p.323-339) generate a clustering-based method to deal with capacitated facility location problem. At first, they determine the allocation plan with minimum cost. Then, they utilize *k*-means clustering-based iterative optimization method to allocate facilities while minimizing demand-weighted distance between demand and associated facility. They also evaluate their methodology with Genetic Algorithm (GA) and state that clustering-based method provides better solutions and lower cost of time. In their study, Li et al. (2012, p.1103-1117) develop a clustering-based scatter search method to determine locations of transshipment points (TPs) which allow multi-commodity flow. They use *k*-means clustering approach to obtain initial solution for their method. In another application, Esnaf and Küçükdeniz (2009, p.259-265) propose a fuzzy clustering-based hybrid method for the multi-facility location problem. The problem is about to deploy multiple facilities for serving demand points. In their method, authors utilize clustering approach to group demand points with the aim of degrading problem from multiple to single facility location problem. They partition demand points into clusters and try to locate single facility in each cluster. Similarly, Sahraeian and Kazemi (2011, p.1098-1102) study the problem of locating multiple facilities among a number of sites whereas all demand points are covered at least one facility. In their three stage method, firstly they determine the minimum number of facilities needed, in other words *k*, with fuzzy set covering approach. Then, they implement *k*-means clustering approach to group demand points into *k*. Finally, they seek the optimal locations of *k* facilities in each group (cluster).

2.4 DISCRETE EVENT SIMULATION (DES)

Simulation is an essential way to evaluate the performance of real-world systems and also assist to design systems for meeting future concerns (Banks, 1999, p.7-13).

Shawki et al. (2015, p.533-540) categorize simulation models mainly as mathematical and physical while defining computer simulation as a sub-type of mathematical modeling application. Computer simulation is a decisive method for evaluating complex systems which requires great budget or enormous effort to construct physically in real. Besides, it is more practical than analytic approaches to deal with problems which consider stochastic aspects. Through the history, computer simulation has been applied in a number of private and public firms (Jahangirian et al., 2010, p.1-13). For example, a distinguished review by Aboueljinane et al. (2013, p.734-750) provides a good perspective about computer simulation models applications which are constructed for improving emergency medical services.

DES is a widely used simulation method to consider systems that have state changes at discrete time intervals (Goldsman and Goldsman, 2015, p.103-109). Discrete event-systems have two major features: (1) randomness, (2) changes at discrete points in time. These systems are applicable to the traditional OR fields which are about queuing and inventory theory such as manufacturing, security, network and airport operations (Fu, 1994, p.199-247). In his survey, Smith (2003, p.157-171) displays studies of DES application about manufacturing, published between 1969 and 2002. Williams and Celik (1998, p.915-920) utilize discrete-event simulation method to evaluate the conveyor systems in automotive final assembly line. In their model, they consider a number of issues such as meeting production goal, flow time, determining bottlenecks and improving system performance. For another example of manufacturing application, Byrne and Heavey (2006, p.420-437) formulate a DES model for analyzing the performance of supply chain with multiple customer, distributors and product families. In military sector, Parsons and Krause (1999, p.1174-1178) use discrete-event simulation method to evaluate logistic issues of U.S. Marine Corps while Burke et al. (2000) develop a discrete-event simulation model, namely Transportation System Capability (TRANSCAP) model, for dealing with the problem of deployment of forces from bases. Similarly, Yıldırım et al. (2009, p.597-611) study military deployment planning problem and formulate simulation model with event graph methodology for analyzing efficiency of deployment plans. They experiment their approach with a given scenario which consider deployment of four battalions from north-western Turkey to southeast border. In another example, Varol and Gunal (2015, p.2037-2049) conduct a hybrid DES and Agent-Based Simulation

(ABS) model to imitate and evaluate counter-piracy operations on the Gulf of Aden. In their model, they study the problem with behaviors of three main actors such as pirates, transporters and naval forces, in a piracy activity. Consequently, they state that helicopter is the most important vehicle in counter-piracy operations. Similarly, Onggo and Karatas (2015, p.254-265) and Onggo and Karatas (2016) develop a simulation model to analyze maritime search operations such as SAR and patrol. In their study, they try to generate an alternative approach to improve search operations with a simulation model that considers behaviors of searcher and target.

In addition to these areas, researchers confront with other application fields that healthcare and emergency medical services (EMS) constitute a large amount. Günal and Pidd (2010, p.42-51) state that there is a notable increase in the number of DES applications in healthcare over ten years and gather recent DES applications about healthcare systems favorably. They concern each study in literature in terms of application area and categorize studies into six groups such as accident and emergencies (A&Es), inpatient facilities, outpatient clinics, other hospital units, whole hospital simulation and other relevant issues. Ingolfsson et al. (2013, p.736-746) develop a DES to analyze the effects of changing ambulances shift organizations from multiple-start system (MS) to single-start system (SS) in which all ambulances start and end their shifts at the same location. They use historical data of 2000 summer and apply model for north-west and central Edmonton, Western Canada. Zhen et al. (2014, p.12-23) apply DES optimization method to analyze the operational efficiency of ambulance deployment and relocation plan in stochastic scene. Furthermore, responding to distress call as quickly as possible is the main goal for an EMS. However, a number of matters such as heavy traffic, unexpected failures and lack of idle resource cause delay and affects the success of operations. Wu et al. (2009, p.1359-1366) study the problem of finding optimal deployment strategies and critical level of demand that requires the ambulance fleet size expanded. They propose a DES model to evaluate EMS of Tainan City while keeping a pre-defined service level as intercepting 90% of calls within 9 minutes. Aboueljinane et al. (2012, p.84) try to improve response time of the French Emergency Medical service (SAMU) in Val-de-Marne department. They develop a DES model to reduce three factors as waiting time, travel time and processing time which determine response time to a distress call. In their study, they experiment their approach with seven

scenarios which consider expanding resource fleet, relocation of existing teams and reducing process time. In a different study, Aboueljinane et al. (2014, p.46-59) use DES in five different strategies to advance same system, SAMU, with the objective of intercepting patients' calls within 20 minutes. Wei et al. (2014, p.207-216) utilize DES to improve ambulance response times in Singapore EMS. They follow three main strategies which consist of relocation ambulances, adding private ambulances and modified dispatch policy and provide a significant improvement for the system. In another study, Nogueira et al. (2014, p.1-12) concentrate on minimizing response times of EMS with optimization and simulation approach. They formulate a multi-objective optimization model to determine deployment plan of ambulances. Then, they define the deployment plan obtained from optimization model as initial plan for DES model. They apply their methodology to EMS in Belo Horizonte, Brazil with six different scenarios which consider dynamic changes in number of ambulances, bases and hospitals.

Maritime SAR operations can be counted as another application field for DES to improve response time to incidents. However, there are few DES studies about maritime SAR systems in the literature. Afshartous et al. (2009, p.1086-1096) propose an optimization and simulation combination methodology to determine locations of the US Coast Guard air stations while minimizing total travel cost (distance). In optimization model, they build the model as *p*-Uncapacitated Facility Location Problem (*p*-UFLP), combination of *p*-MP and UFLP. Then, they apply simulation method to evaluate the solutions of optimization model. In simulation model, they formulate a statistical model which generates stochastic distress calls from an inhomogenous Poisson process, using historical data of the year 2000, in order to utilize in simulation model. As another simulation application in maritime SAR, Goerlandt et al. (2013, p.1-6) identify the maritime search and rescue operation as a multi-server, multi-customer queuing system that incidents/incident locations are customers and boats at ports are servers. They develop a DES model to provide a decision-support tool for The Finnish Lifeboat Institution in determining total number and type of boats at each station for SAR organization. For model inputs, they utilize historical incident data from the year 2007 to 2010 in Gulf of Finland and categorize incidents into 21 different types. In addition, they import wave conditions at incident locations into model for imitating real-world state which is an important

aspect in determining which type of boat should be assigned. Under these circumstances, they try to locate 29 boats to 11 different stations along Gulf of Finland.

3 METHODOLOGY

Our methodology consists of two main steps as shown in Figure 3.1. In this chapter, we will describe our optimization methodology and simulation model.

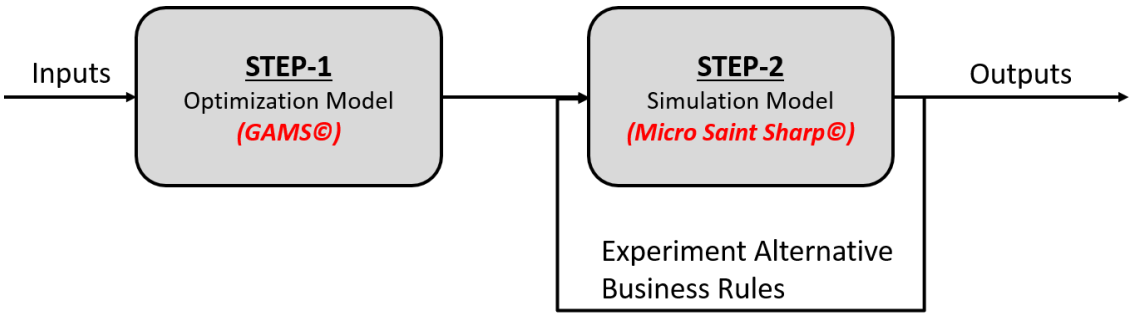

Figure 3.1: Methodology structure.

3.1 OPTIMIZATION METHODOLOGY

Optimal allocation of SAR resources is a strategic process which is to be carried out with an excellent planning to respond distress calls as quickly as possible. It is clear that the lower response time brings out higher survival rates in an incident. Furthermore, in step of establishing allocation plan, decision-makers must take some key factors into consideration:

- Historical data of incidents in the area of interest,
- Types of incidents, requirements and severity,
- SAR resource capability,
- Geographical factors,
- Available stations (ports).

In this thesis, all these factors were taken into account and optimization model was formulated with the methodology displayed in Figure 3.2. Briefly, this methodology includes three major steps: (Step-1) determining incident type weights, (Step-2) the ZDM and (Step-3) the optimization model.

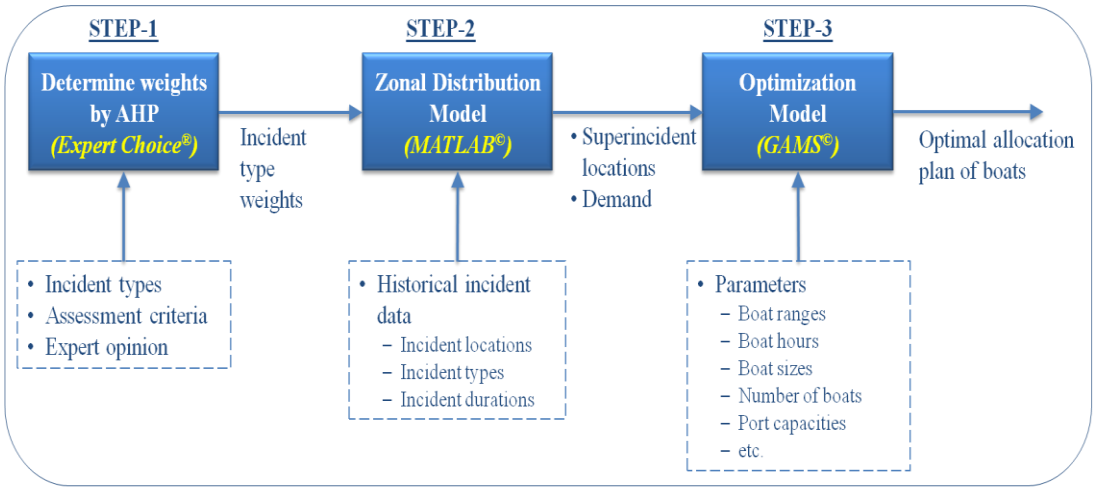

Figure 3.2: Steps of optimization methodology.

3.1.1 Weight Determination

In a number of previous works about search and rescue, researchers do not consider the severity of each type of incidents, although they utilize different types of incidents in their works. Maritime incidents bring out many perverse results in humanity, ecological and economic issues. As it is clear, severity and magnitude of these results depend on incident type. More severe incidents require well organized and diverse SAR operation. Thus, incident types should be prioritized for planning and conducting SAR operations neatly, especially if there are finite utilities.

In our historical data of the Aegean Sea, we confront with eight different incident types such as drifting, capsizing, grounding, fire, collision, flooding, missing, and medical assistance. Naturally, each type of incident has individual characteristics according to several criteria. For example, unexpected death rates would occur in a capsizing incident while a fire incident causes a possible major damage in environment. Thus, we decide to rank each incident type in accordance with some criteria. After discussing with coast guard officers, we determine four criteria such as fatality, material damage, response arduousness and environmental impact which influence the severity/ranking of an incident (see Table 3.1).

Table 3.1: Criteria definition.

Criterion Name	Definition
Fatality	The deaths and injuries.
Material damage	The economic loss generated by the incident.
Response arduousness	Complexity and difficulties of operation.
Environmental impact	Damage on the environment, such as pollution, effects on habitats, etc.

Then, we construct the decision tree that represents hierarchical relationships between each element in the ranking problem (see Figure 3.3).

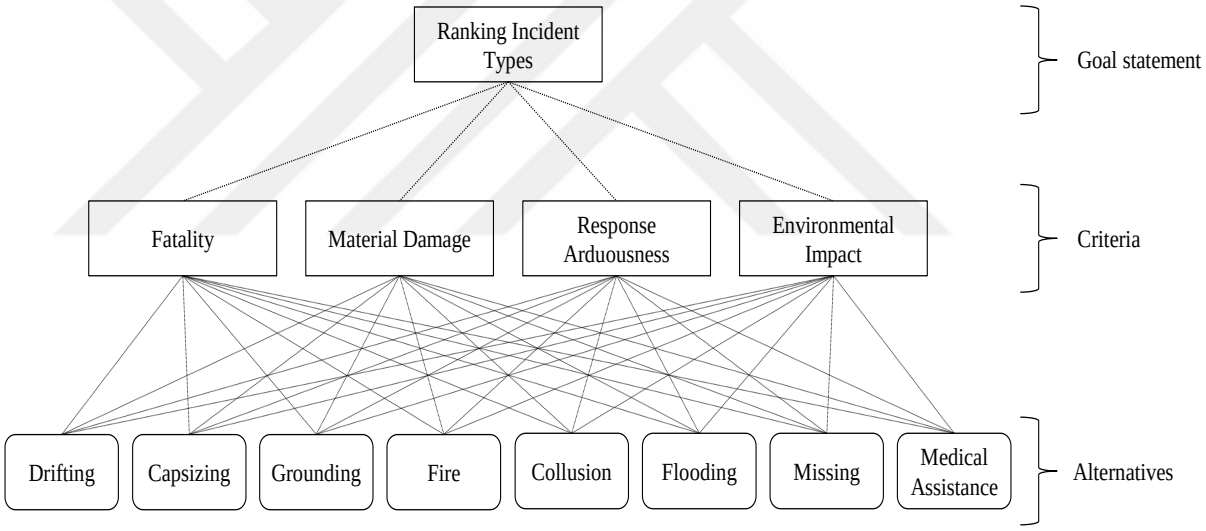

Figure 3.3: The decision tree with goal statement, criteria for analysis, and alternatives (incident types).

Next, we apply AHP technique with Expert Choice® to determine relative importance of each incident. Finally, results of AHP applications display that incident type with largest weight value is the most severe incident.

3.1.2 Zonal Distribution Model (ZDM)

The main input of a facility location problem is the data of demand points. Firstly, we plotted all incidents at its actual location to determine demand points. However, large input data size makes the ILP model harder. In addition, this also causes high

data collection cost, modeling cost, computing cost, confidentiality concerns and data statistical uncertainty while implementing in model for various purposes (Francis et al., 2009). For example, if there are 1000 demand points and 20 ports, 1000x20=20000 maritime distances must be calculated as input parameters. Maritime distances are not Euclidian distances and these distances should be computed with consideration of obstacles (land, island and depth).

Another reason of utilizing a clustering algorithm is to use the representative weighted locations of historical incidents based on their density and severity, rather than their exact locations. We believe that solving the optimization model by using the "exact" locations of the incidents would be a repetition of the past in terms of model input data. Instead, we solve the optimization problem by using clusters and relied on the solution as an effective allocation plan for the expected future incidents. We believe that this approach would enable the methodology to serve as a more flexible (one may prefer to use another clustering technique) and representative (help users to distinguish the most problematic and severe regions) tool for any given SAR allocation situation. Thus, we decided to use ZDM model to determine the amount and location of demand. As ZDM requires, we aggregate incidents into regions.

K-means clustering algorithm is a prevalent technique to aggregate location data. In this method, algorithm tries to assign *n* input data, $X = \{x_1, x_2, ..., x_n\}$, into its nearest cluster center among *K* sets, $C = \{c_1, c_2, ..., c_k\}$ with the objective of minimizing the sum of error squared, $Z = \sum_{i=1:n} \min_{j \in \{1,...k\}} \left\| x_i - c_j \right\|^2$. In classical *k*-MCA, each input data has equal importance to determine cluster centroids. However, in a number of problems, each input data could have more relative importance than other ones. In our study, each type of incident has relative importance (weights) as mentioned in Section 3.1.1 and it is clear that these weights should be considered while clustering and determining centers. Thus, we utilize "*weighted k-means clustering algorithm*" (*wk*-MCA) (Kerdprasop et al., 2005, p.488-497) to determine weighted center points, called "*superincident*", of each region to represent all incidents in that.

Like classical *k*-means clustering algorithm, *wk*-MCA has also three main steps;

(1) Initial partition with *k*-cluster,

(2) Assigning each input data to nearest cluster center,

$$m\left(c_j \mid x_i\right) = \frac{\left\| x_i - c_j \right\|^2}{\sum_{j=1:k} \left\| x_i - c_j \right\|^2} \tag{3.1.}$$

where $m\left(c_j \mid x_i\right)$ is a function for represent the membership of input data x_i to cluster center c_j.

(3) Determining new cluster centers, c_j^*, with existing membership and weights, $w\left(x_i\right)$.

$$c_j^* = \frac{\sum_{i=1:n} m\left(c_j \mid x_i\right) w\left(x_i\right) x_i}{\sum_{i=1:n} m\left(c_j \mid x_i\right) w\left(x_i\right)} \tag{3.2.}$$

(4) Re-apply step 2 and step 3 until obtaining stable clusters (Kerdprasop et al., 2005, p.488-497).

We generate regions and determine *superincidents* as follows:

$k \in K$: Set of incidents.

$i \in I$: Set of incident types.

$z \in Z$: Set of (superincident) zones.

$K_{zi} \subset K$: Set of incidents of type $i \in I$ that occurred in zone $z \in Z$.

$T = \left\{t_1, t_2, ..., t_{|K|}\right\}$: Set of incident operation times (hrs) where t_k denotes its k^{th} element.

w_i : weight of incident type *i*. (obtained from Step-1).

We determine the number of regions with *the rule of thumb method*, $|Z| \approx \sqrt{|K|/2}$, which is simple and suitable for all types of data (Kodinariya and Makwana, 2013, p.90-95). For each zone $z \in Z$, the *wk*-MCA generates a weighted-centroid, which we call as a "*superincident*". Each superincident is assigned with a location (latitude and longitude) and an aggregated yearly demand D_{zi} for each incident type $i \in I$ in zone $z \in Z$. D_{zi} is simply obtained as:

$$D_{zi} = \sum_{k \in K_{zi}} t_k, \forall z \in Z, i \in I \tag{3.3.}$$

3.1.3 Optimization Model

In this step, we develop a mo-MIP resource allocation model. The model is formulated with sets and indices, parameters, variables, constraints and objective function explained below.

3.1.3.1 Sets and Indices

$i \in I$: Set of incident types.

$p \in P$: Set of candidate ports.

$z \in Z$: Set of (superincident) zones.

$b \in B$: Set of boat types.

$B_i \subset B$: Set of boat types that are appropriate for incident type $i \in I$.

$B_p \subset B$: Set of boat types that are allowed at port $p \in P$.

$B_{pz} \subset B$: Set of boat types that can respond to incidents in zone $z \in Z$ from port $p \in P$. (determined considering the maximum range of boats)

3.1.3.2 Parameters

cf_{bp} = Yearly fixed cost of utilizing one type *b* boat at port *p* ($/year).

cv_b = Variable cost of operating one type *b* boat for one hour ($/hr).

U_b = Total available number of type *b* boats.

$u_b^{\min}$ = Minimum allowable number of type *b* boats at a port if allocated.

$u_b^{\max}$ = Maximum number of type *b* boats that can be allocated to a port.

S_b = Annual Operation Capacity (AOC) of a single type *b* boat (hrs).

r_b = Maximum allowable percentage of AOC that can be exceeded for type *b* boat.

γ_b = Multiplier (for s_{bpzi}) to provide minimum allowable yearly total task time for boats of type *b* assigned from a port to a zone for a single incident type (hrs).

w_i = Weight of incident type *i* (obtained from Step-1).

D_{zi} = Aggregated yearly demand in zone *z* for incident type *i* (hrs) (obtained from Step-2).

n_{zi} = Number of type *i* incident aggregated to zone *z* (obtained from Step-2).

rt_{bpz} = Response time of a type *b* boat from port *p* to zone *z* (hrs).

crt_i = Critical response time threshold for incident type *i* (hrs).

L_p = Physical capacity of port *p* (mts).

ℓ_b = Length of type *b* boat (mts).

FB = Annual fleet operating budget (M$).

3.1.3.3 Decision Variables

x_{bp} = Number of type *b* boats allocated to port *p* (integer).

y_{bp} = Variable indicating whether or not type *b* boats are utilized in port *p* (binary).

s_{bpzi} = Total number of yearly hours (supply) of type *b* boats assigned from port *p* to zone *z* for incidents type *i* (hrs).

λ_{bpzi} = Variable indicating whether or not type *b* boats are utilized in port *p* to zone *z* for incidents type *i* (binary).

$dev^{crt+}_{bpzi}, dev^{crt-}_{bpzi}$ = Positive and negative deviations associated with critical response time threshold for each individual incident type *i* in zone *z* responded from port *p* by type *b* boat (hrs).

dev^{fb+}, dev^{fb-} = Positive and negative deviations associated with the annual fleet operating budget ($).

$dev^{s+}_{bp}, dev^{s-}_{bp}$ = Positive and negative deviations associated with the AOC for type *b* boats in port *p* (hrs).

3.1.3.4 Constraints

3.1.3.4.1 Boat Capacity Constraint

Constraint (3.4.) ensures that the total allocated boats cannot exceed the boats on hand:

$$\sum_{p \in P} x_{bp} \leq U_b, \quad \forall b \in B \tag{3.4.}$$

3.1.3.4.2 Minimum and Maximum Boat Constraints

During an annual period, not all boats are operational 100% of the time mainly

because of scheduled events (such as overhauling, maintenance, exercises, sea trials) or unexpected situations (such as breakdowns, crew shortage). In order to maintain a certain level of service without interruption, the business rule of "*minimum* number of boats requirement" is implemented. Constraint (3.5.) ensures that for each type *b* boat assigned to a port, there should be at least $u_b^{\min}$ and at most $u_b^{\max}$ of it respectively.

$$y_{bp}u_b^{\min} \le x_{bp} \le y_{bp}u_b^{\max}, \quad \forall b \in B, p \in P \tag{3.5.}$$

3.1.3.4.3 Supply-Demand Relationship Constraints

Constraint (3.6.) ensures that total supply (from all boat types in all ports) meets demand in each zone *z* for each incident type *i*. We should also note that for strategic long run planning purposes, forecasted number of incidents could be used in our ZDM to determine demand.

$$\sum_{p \in P}\sum_{b \in B} s_{bpzi} = D_{zi}, \quad \forall z \in Z, i \in I \tag{3.6.}$$

3.1.3.4.4 Variable λ_{bpzi} Definition Constraints

The technical constraint (3.7.) determines the minimum allowable s_{bpzi} hours. M is a relatively large number.

$$\lambda_{bpzi}\gamma_b \le s_{bpzi} \le \lambda_{bpzi}M, \quad \forall b \in B, p \in P, z \in Z, i \in I \tag{3.7.}$$

3.1.3.4.5 s_{bpzi} and x_{bp} Relation Constraint

Technical constraint (3.8.) ensures that total supply originating from type *b* boats in port *p* can take a positive value only if x_{bp} is positive. M is a relatively large number.

$$\sum_{z \in Z}\sum_{i \in I} s_{bpzi} \le x_{bp}M, \quad \forall b \in B, p \in P \tag{3.8.}$$

3.1.3.4.6 Port Size Capacity Constraint

All ports have a capacity in meters to berth units naturally. Constraint (3.9.) limits the number of assigned boats for a port as follows:

$$\sum_{b \in B} x_{bp}\ell_b \le L_p, \quad \forall p \in P \tag{3.9.}$$

3.1.3.4.7 Appropriate Boat-Port Constraint

Business rules dictate that certain boat types are not allowed at certain ports. Constraint (3.10.) makes sure that a port only gets boats that are allowed at that port.

$$\sum_{b|b\in B\setminus B_p} x_{bp} = 0, \quad \forall p \in P \tag{3.10.}$$

3.1.3.4.8 Appropriate Boat-Incident Constraint

Due to the fact that each incident may require special equipment and features such as fire-fighting, towing, endurance, high speed etc., Constraint (3.11.) ensures appropriate boat type-incident type assignments as follows:

$$\sum_{b|b\in B\setminus B_i} \sum_{p\in P} \sum_{z\in Z} s_{bpzi} = 0, \quad \forall i \in I \tag{3.11.}$$

3.1.3.4.9 Appropriate Boat-Distance Constraint

A boat can only respond incidents within its maximum operating range. Constraint (3.12.) dictates this rule as follows:

$$\sum_{b|b\in B\setminus B_{pz}} \sum_{i\in I} s_{bpzi} = 0, \quad \forall p \in P, z \in Z \tag{3.12.}$$

3.1.3.4.10 Response Time Deviations from Critical Response Time Threshold

Constraint (3.13.) represents the goal of minimizing response time over critical response time threshold.

$$rt_{bpz}\lambda_{bpzi} + dev_{bpzi}^{crt-} - dev_{bpzi}^{crt+} = crt_i, \quad \forall b \in B, p \in P, z \in Z, i \in I \tag{3.13.}$$

3.1.3.4.11 Supply Excess\Shortage from Capacity

The goal for minimizing capacity excess and shortage for each type *b* boat at each port *p* is given by Constraint(3.14.). The workload of a boat consists of the times it spends at the incident locations and traveling back and forth between ports and incident locations.

$$\sum_{z\in Z} \sum_{i\in I} \left(s_{bpzi} + 2n_{zi} rt_{bpz}\lambda_{bpzi} \right) + dev_{bp}^{s-} - dev_{bp}^{s+} = S_b x_{bp}, \quad \forall b \in B, p \in P \tag{3.14.}$$

3.1.3.4.12 Cost Deviations from Planned Budget

One common objective used in many resource allocations related studies is to minimize the fixed and variable costs associated with locating the new facility (Tsouros and Satratzemi, 1994, p.373-377). In our case, we define our "*fleet operating cost*" as the sum of fixed and variable costs of boat operations. At the end of each fiscal year, the "*annual fleet operating budget*" is declared and distributed over available boats in the following year. Constraint (3.15.) measures the deviations from budget as follows:

$$\left(\sum_{b \in B} \sum_{p \in P} cf_{bp} x_{bp} + \sum_{b \in B} \sum_{p \in P} \sum_{z \in Z} \sum_{i \in I} cv_b s_{bpzi} \right) + dev^{fb-} - dev^{fb+} = FB \qquad (3.15.)$$

3.1.3.4.13 Limit on the AOC Exceeded

Constraint (3.16.) makes sure that the positive deviation associated with the AOC cannot exceed the maximum allowable time for each type *b* boat in port *p*.

$$dev_{bp}^{s+} \leq S_b x_{bp} r_b, \quad \forall b \in B, \forall p \in P \qquad (3.16.)$$

3.1.3.4.14 Variable Type Declarations

$$x_{bp} \in \{0,1,2,...\}, \quad \forall b \in B, p \in P \qquad (3.17.)$$

$$y_{bp} \in \{0,1\}, \quad \forall b \in B, p \in P \qquad (3.18.)$$

$$\lambda_{bpzi} \in \{0,1\}, \quad \forall b \in B, p \in P, z \in Z, i \in I \qquad (3.19.)$$

$$s_{bpzi}, dev_{bpzi}^{crt+}, dev_{bpzi}^{crt-} \geq 0, \quad \forall b \in B, p \in P, z \in Z, i \in I \qquad (3.20.)$$

$$dev^{fb+}, dev^{fb-} \geq 0 \qquad (3.21.)$$

$$dev_{bp}^{s+}, dev_{bp}^{s-} \geq 0, \quad \forall b \in B, p \in P \qquad (3.22.)$$

3.1.3.5 Objective Function

The multi-objective function, given by equation (3.23.), attempts to minimize three terms. The first term measures the total weighted deviations resulting from exceeding critical response times. The second term represents the deviation resulting from exceeding the budget. The final term measures the total deviation of supply from capacity. Minimizing both positive and negative deviations aims to balance workload

such that for each boat type assigned to a port the excess and shortage operation hours over annual capacity is minimized.

$$Min\ \ z = \omega_1\theta_1 \sum_{b\in B}\sum_{p\in P}\sum_{z\in Z}\sum_{i\in I} w_i n_{zi} dev^{crt+}_{bpzi} + \omega_2\theta_2 dev^{fb+} + \omega_3\theta_3 \sum_{b\in B}\sum_{p\in P}\left(dev^{s+}_{bp} + dev^{s-}_{bp}\right) \quad (3.23.)$$

For each goal $g \in \{1,2,3\}$, ω_g and θ_g represent the weights assigned by the decision maker, and the normalization factor, respectively. The normalization factors θ_g are used to scale the objective function terms which have different magnitudes, thus enable to get consistent solutions with the weights ω_g.

3.1.3.6 Scalarization of the Objective Function Components

Even though there are a number of solution techniques for multi-objective problems, we choose weighted sum method to solve our model technically. However, each section of the objective function has a different scale and this difference could affect the correctness of results. Thus, the normalization of the objective function component is necessary.

Regarding the type of our optimization model, it is proper to utilize the notion of Pareto optimality which provides no other solutions that improves at least one part of the objective function without degradation in another (Zitzler and Thiele, 1999, p.257-271). At this point we use the normalization technique described in (Grodzevich and Romanko, 2006, p.89-101). In this technique, two special points are calculated for each section of the objective function individually, namely Nadir and Utopia points. Utopia point, z^U, represents the lower bound of mentioned section and could be obtained by minimizing each section *i* as follows:

$$z^* = \arg\min_x \left\{ f_i(x) : x \in \Omega \right\} \quad (3.24.)$$

Nadir Point, z^N, represents the upper bound of each objective section *i* and could be defined as:

$$z_i^N = \max_{1\le j\le k}\left(f_i\left(x^{[j]}\right)\right), \quad \forall i = 1,...,k \quad (3.25.)$$

After calculations of these points, normalization coefficient value for each section, θ_i, could be determined as in equation (3.26.):

$$\theta_i = \frac{1}{z_i^N - z_i^U} \tag{3.26.}$$

Each of these coefficient values, θ_i, normalize scales and make the magnitude of each sections equalized. Furthermore, it is clear that, utilization of normalization technique bounds the objective function value as:

$$0 \leq \frac{f_i(x) - z_i^U}{z_i^N - z_i^U} \leq 1 \tag{3.27.}$$

3.2 SIMULATION MODEL

In this thesis, we identify Maritime SAR process as server-to-customer queuing system which incidents/demands are customers and boats/resources are servers and perform simulation methodology to evaluate system. Simulation optimization technique requires advanced computers and takes respectable time to conduct. Thus, we apply DES model to test the performance of optimization model.

Our simulation model is constructed with three stages:

- Determining inputs,
- Model formulation,
- Outputs.

3.2.1 Determining Inputs

In our simulation model, we utilize three inputs: (1) Incidents/demands, (2) Ports/stations, (3) SAR boats/resources.

In stage of determining incidents/demands, we use historical incident data of the area of interest. However, utilizing all incidents individually makes model more complex as in optimization model. Thus, we divide all responsibility area into rectangular grids with respect to incident density. Each grid represents a sub-area with its individual incident patterns. It is clear that generating smaller grids approximates the system to real case. However, geographical features of the area could not let it to do easily. More importantly, generated smaller grid structure makes it enable to represent risky sub-regions. Then, we analyze each grid separately to generate an

incident inter-arrival time distribution which fits to incident data in each grid. Also, we assume that incidents are distributed in sub-areas random uniformly.

For other inputs, we take the data of activated ports and assigned boats from optimization model's outputs. We implement allocation plan of optimization model as inputs in simulation model.

3.2.2 Process Flow

Maritime SAR operations starts with a distress call which comes to operation center. Decision-makers in operation centers evaluate the situation and pass all related information about incident to nearest port in which there is an idle capable boat. When all information is recorded, port dispatches a capable boat with respect to incident type. For example, decision-makers must assign a faster boat to medical assistance incident for transferring patient to nearest medical services as quickly as possible. Then, boat conducts the operation unless it is in need of refueling otherwise it turns back to port for refueling. After that, it goes on duty if requires, otherwise, stands in port for next duties.

In our DES model, a SAR process begins with a distress call to operation center about incident generated in a gird. Then, model calculates distances from incident position to each port and sorts them. After that, operation center checks ports in ascending order for an idle capable boat. If the operation center determines port and boat type to assign, designated boat dispatches for conducting duty. However, in some cases, there could be more than one capable and idle boat for a duty. Thus, we implement two different selection criteria for determining which boat to assign among capable ones, remaining capacity and speed.

3.2.2.1 Remaining Capacity

The main goal of this criterion is to maintain balanced workload among boats. Hence, operation center selects the capable one with higher remaining capacity, even if there is a faster idle boat. Furthermore, we try to represent the third section of objective function in optimization model with this criterion. After selection, the boat conducts the duty. However, in case of no idle boat for a duty, incident waits for an idle boat in the queue (FIFO). Model executes this process flow for 24x365=8760 hours which imitate a year (Figure 3.4).

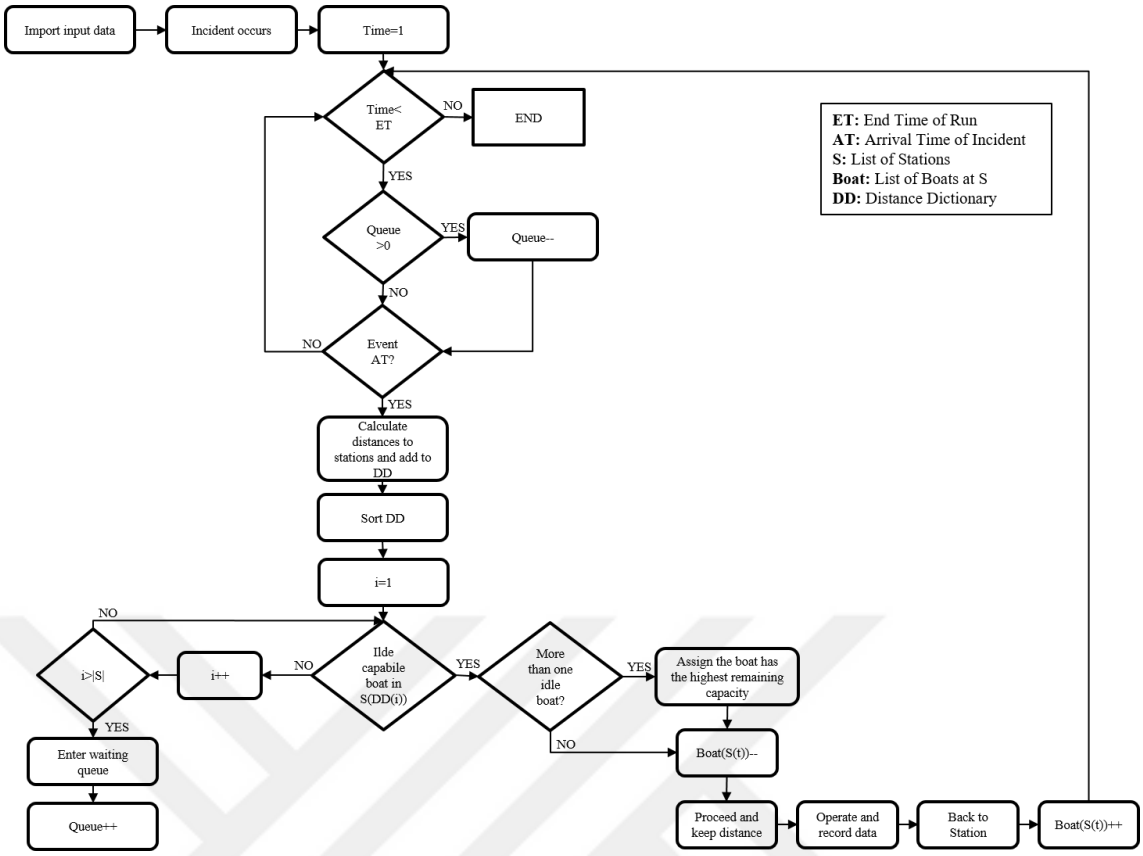

Figure 3.4: Flow chart of simulation model with the "Remaining Capacity" selection criterion.

3.2.2.2 Speed

With this criterion, the model follows a greedy approach by assigning the available fastest boat for each incident. When an incident occurs and there is more than one idle boat, the model (operation center) selects the fastest idle boat among capable ones. It is clear that this approach could help to reduce response times. However, giving priority to faster ones could also cause consuming faster boats toward the end of simulation model. After selection, the boat conducts the duty. However, in case of no idle boat for a duty, incident waits for an idle boat in the queue (FIFO). Model executes this process flow for 24x365=8760 hours which imitate a year (Figure 3.5).

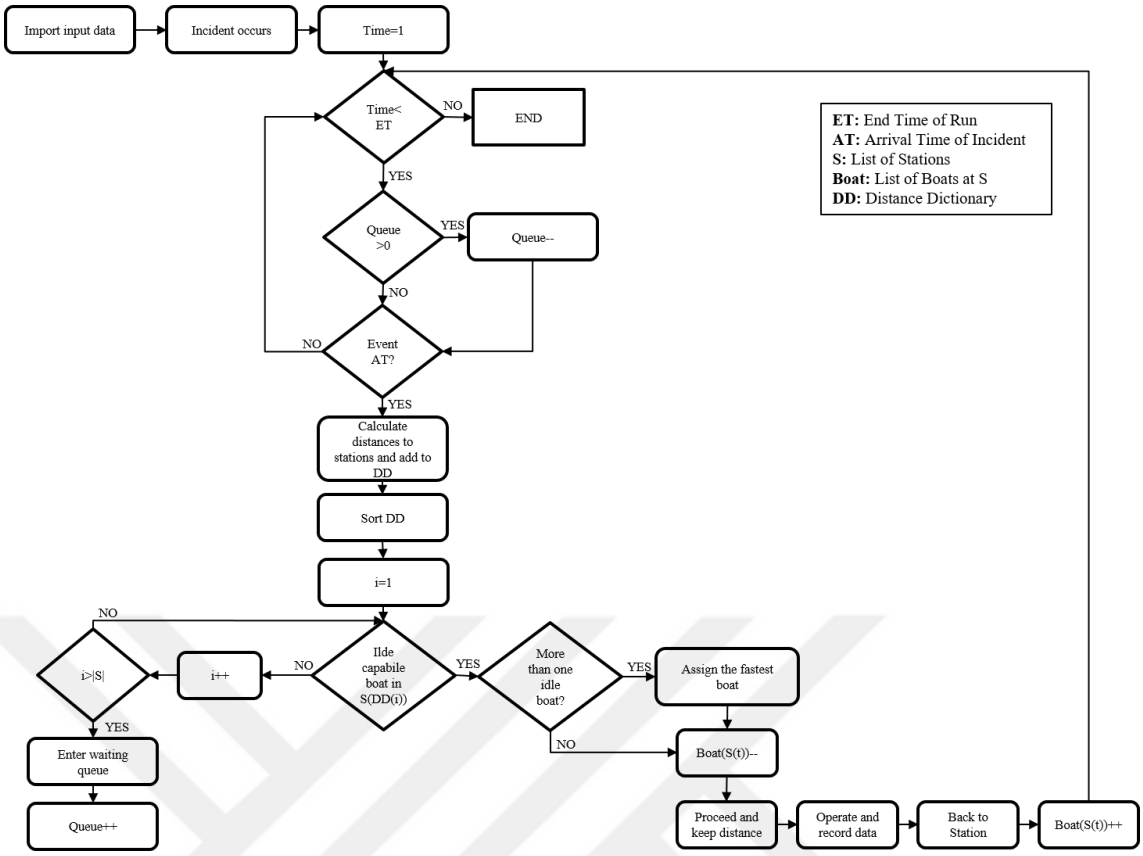

Figure 3.5: Flow chart of simulation model with the "Speed" selection criterion.

3.2.3 Outputs

We use our simulation model to evaluate the performance of the optimization model in terms of 12 measure of effectiveness (MoE) values summarized in Table 3.2.

Table 3.2: Model outputs.

MoE_1	Total delay (hrs)	$\triangleq$ Sum of positive deviations associated with the critical reaction time threshold
MoE_2	Total weighted delay (hrs)	$\triangleq$ Sum of weighted positive deviations associated with the critical reaction time threshold
MoE_3	Shortage on the budget (M$)	$\triangleq$ Positive deviation associated with the annual budget
MoE_4	Ratio of budget used (%)	$\triangleq \frac{\text{used fleet budget}}{\text{planned fleet budget}}$
MoE_5	Total excess AOC (hrs)	$\triangleq$ Sum of negative deviations associated with the AOCs

Table 3.2 (Continue)

MoE_6	Total shortage on the AOC (hrs)	$\triangleq$ Sum of positive deviations associated with the AOCs
MoE_7	Total deviation on the AOC (hrs)	$\triangleq$ Sum of (positive and negative) deviations associated with the AOCs
MoE_8	Ratio of utilized fleet size (%)	$\triangleq \frac{\text{total number of boats utilized}}{\text{total number of boats available}}$
MoE_9	Ratio of incidents intercepted (%)	$\triangleq \frac{\text{total number of incidents intercepted}}{\text{total number of incidents occured}}$
MoE_{10}	Ratio of demands satisfied (%)	$\triangleq \frac{\text{total number of demands satisfied}}{\text{total number of demands generated}}$
MoE_{11}	Total reaction time	$\triangleq$ Sum of reaction times to incidents intercepted
MoE_{12}	Reaction time per incident	$\triangleq \frac{\text{total reaction time}}{\text{total number of incidents intercepted}}$

4 CASE STUDY: ALLOCATION OF SAR RESOURCES ALONG THE AEGEAN SEA

Turkish Government declared Turkish SAR Plan, which establishes all responsibilities and organizations in agreement with international treats, in the year 2001 and registered it with the relevant International Maritime Organization (IMO) documents, namely, IMO Global SAR Plan. According to Turkish SAR plan, TurCG Command has the responsibility for coordinating and conducting SAR activities/operations in the Turkish SAR Zone, which is divided into the following four sub-responsibility areas: the Black Sea, the Sea of Marmara and Adjacent Straits, the Aegean Sea and the Mediterranean Sea. Each one of these sub-regions has individual properties. However, The Aegean Sea differs from the others with respect to a number of characteristics and traffic density. Firstly, the Aegean Sea is the only way from and to the Black Sea for navigation and transportation. In their study, Miliou et al. (2012) state that 72,919 vessels of which 65% were cargo ships, 21% were tankers, 5% were passenger ships and 9% were others passed the Aegean Sea via three channels: Mykonos-Ikaria, Ikaria-Samos and Evia-Andros. Secondly, having more than 3000 islands in various sizes makes it attractive for cruise tours, water sports and yachting. Finally and most importantly, illegal-border crossing activities have considerable impact on the traffic density. The turmoil in the Middle East has led to a substantial increase in the number of refugees and migrants crossing the Mediterranean since 2013 (UNHCR Global Appeal, 2015). Immigrants follow two main routes to cross EU borders illegally, being The Aegean Sea and that of Libya-to-Italy. Giuliani (2015) states that the number of immigrants detected in the Aegean Sea increased from 2,683 to 10,445 only in 2014. Under these circumstances, heavy traffic on narrow and shallow waters, like in the Aegean Sea, undoubtedly brings along a respectable increase of risk in maritime safety (Goerlandt and Kujala, 2011, p.91-107).

Historical incident data obtained from TurCG displays that 1933 incidents occurred in the Aegean Sea (Turkish SAR Responsible Region) between 2009 and 2014. As shown in Figure 4.1, of those incidents, 60% were drifting/machinery breakdown notably associated with illegal-border crossing and yachting/surfing activities, 21% were medical assistance, 9% were missing, 4% were capsizing, 3% were flooding,

2% were grounding, 0.8% were fire and 0.2% were collision.

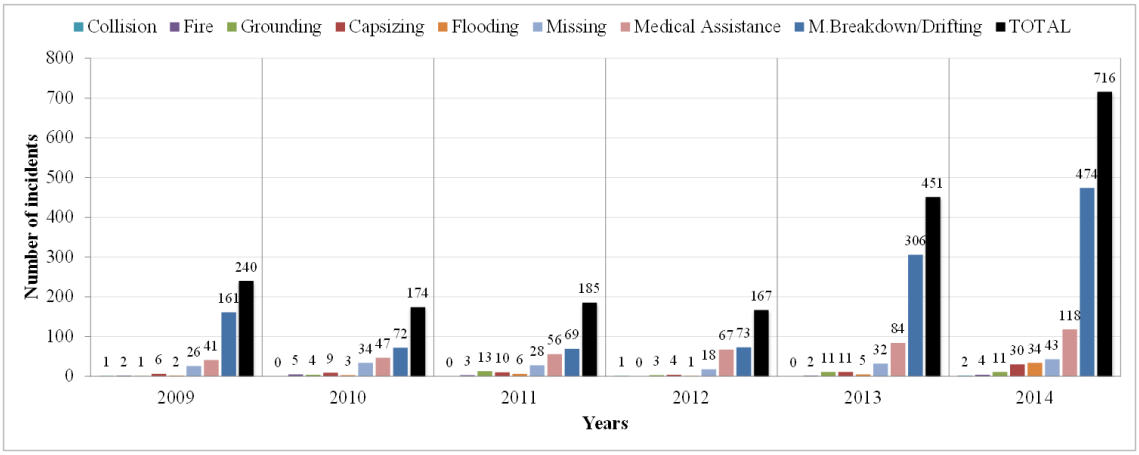

Figure 4.1: Number of incidents occurred between 2009 and 2014 in the Aegean Sea.

In TurCG fleet, there are three types of platforms to conduct scheduled and emergency duties. If we categorize these platforms as surface units and aircrafts, the former consists of two different types: (1) SAR ship (single type) with a length of more than 85 mts., (2) SAR boats (12 different types) under 45 mts. in length and aircrafts are airplanes and helicopters.

In this thesis, we focus on locating surface units among the pre-determined ports, though aircrafts are also important platforms to deal with emergency cases at sea. We try to optimally locate the SAR ship (with a length of more than 85 mts.) and 8 types of SAR boats (the ones that can operate in the confined and shallow waters of the Aegean Sea) to 25 different pre-determined candidate ports along the coast of the Aegean Sea with the help of historical incident data from the year 2014.

We implement weight determination with a decision support tool, Expert Choice® and ZDM method (data aggregation) in MATLAB® R2013a for the optimization model. Then we solve ILP model in the General Algebraic Modeling System (GAMS©) environment using CPLEX 12.2.0.2. In addition, the simulation model is built and applied using Micro Saint Sharp© version 3.7. In this chapter, we display the case study in two sections, (1) optimization model and (2) simulation model, since each of them has individual approaches especially in determining inputs.

4.1 OPTIMIZATION MODEL

4.1.1 Data Collection

As mentioned in the previous section, TurCG is responsible for planning, coordinating and conducting SAR operations in the Turkish SAR Responsible Regions around the mainland. While conducting SAR operations, TurCG collects important information about incidents intercepted. The Operation Management Center records detailed data about incidents such as date and time, location (latitude-longitude), type, assigned boats, operation time, departure and arrival time of boats, operation details, geographical and weather conditions, the number of surviving, killed or injured people, etc.

In this thesis, we use historical incident data, covering those in the Aegean Sea sub-responsible region of the year. The said data is obtained from TurCG and contains 716 incidents with 8 different types as shown in Figure 4.2.

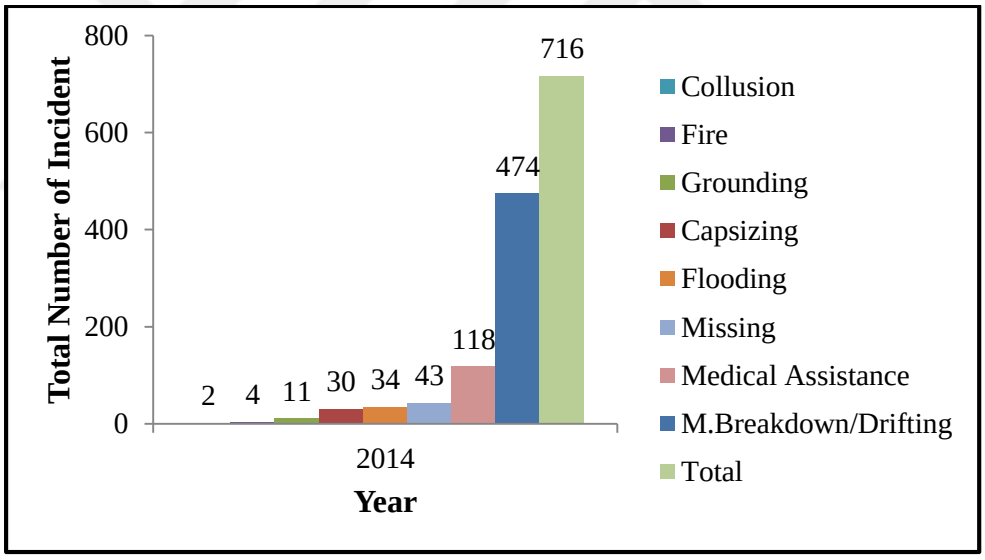

Figure 4.2: Number and type of incidents having occurred in 2014.

We utilized the SAR ship and 8 different types of SAR boats referring to a number of characteristics, such as total number, AOC, minimum and maximum allowable number of boats at a port, range, operation speed, length, fixed annual costs and variable costs per hour**.** Besides, we determined the capacity (mts) and suitability data for 25 candidate ports in the Aegean coastline. We name the boats as *B*1, *B*2,…, *B*9 and the ports as *P*1, *P*2,…, P25.

4.1.2 Weight Determination

We determined relative importance/weights of eight incident types by AHP methodology using Expert Choice®. In this step, we conducted pairwise comparisons for determining weights according to the views of TurCG officers who attend SAR missions.

First, we compared each criterion for determining the relative importance to utilize, while considering alternatives. Results in Table 4.1 indicate that criteria of "Fatality", "Environmental Impact", "Response Arduousness" and "Material Damage" get the values of 0.542, 0.247, 0.134 and 0.077, respectively. Therefore, "Fatality" and "Environmental Impact" are the main criteria that should be considered while ranking incident types with that, "Response Arduousness" and "Material Damage" have the least weights. In addition, the inconsistency value is calculated as 0.03.

Table 4.1: Pairwise comparison matrix of criteria.

	Fatality	**Material Damage**	**Response Arduousness**	**Environmental Impact**	**Relative Importance**
Fatality	1	5	4	3	0.542
Material Damage	1/5	1	1/2	1/4	0.077
Response Arduousness	1/4	2	1	1/2	0.134
Environmental Impact	1/3	4	2	1	0.247
Inconsistency					**0.03**

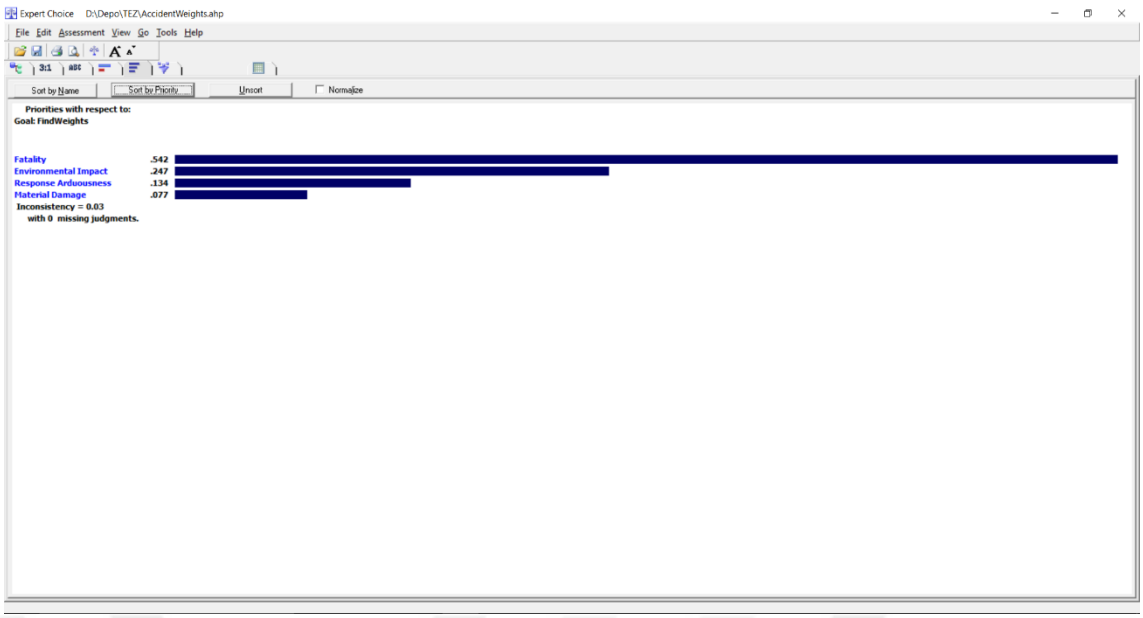

Figure 4.3: Weights of each criterion in descending order.

Table 4.2, Table 4.3, Table 4.4 and Table 4.5 display comparisons of each alternative with fatality, material damage, response arduousness and environmental impact, respectively. Also, Figure 4.4, Figure 4.5, Figure 4.6 and Figure 4.7 display incident type weights in descending order with respect to each criterion.

Table 4.2: Comparison of alternatives with respect to criterion "Fatality".

	Drifting	**Capsizing**	**Grounding**	**Fire**	**Collision**	**Flooding**	**Missing**	**Med.Asst.**	**Relative Imp.**
Drifting	1	1/4	1	1/5	1/4	1/4	1/4	1/4	**0.035**
Capsizing	4	1	5	1	2	3	3	2	**0.235**
Grounding	1	1/5	1	1/4	1/3	1/3	1/3	1/4	**0.038**
Fire	5	1	4	1	2	3	2	1/2	**0.188**
Collision	4	1/2	3	1/2	1	2	1	1	**0.125**
Flooding	4	1/3	3	1/3	1/2	1	1/3	1/3	**0.076**
Missing	4	1/3	3	1/2	1	3	1	1	**0.129**
Med.Asst.	4	1/2	4	2	1	3	1	1	**0.172**
Inconsistency									**0.04**

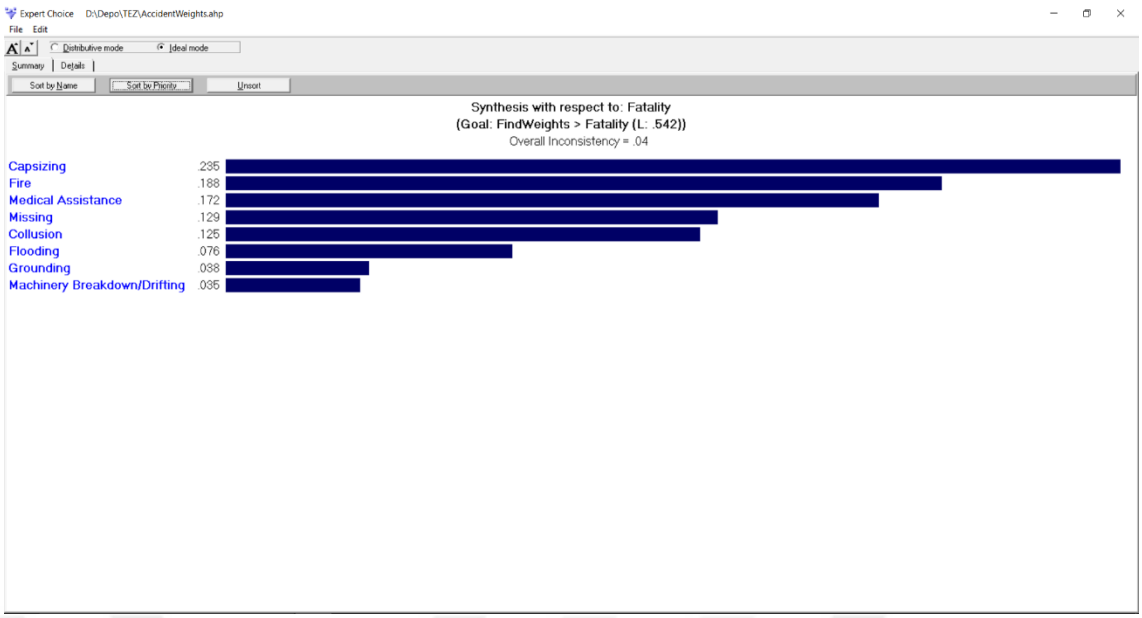

Figure 4.4: Incident type weights in descending order with respect to the "Fatality" criterion.

Table 4.3: Comparison of alternatives with respect to the "Material Damage" criterion.

	Drifting	Capsizing	Grounding	Fire	Collision	Flooding	Missing	Med.Asst.	Relative Imp.
Drifting	1	1/5	1/3	1/4	1/3	1/3	1/2	3	**0.048**
Capsizing	5	1	4	3	3	3	3	4	**0.305**
Grounding	3	1/4	1	1/3	1/3	1/3	2	4	**0.086**
Fire	4	1/3	3	1	2	2	3	4	**0.190**
Collision	3	1/3	3	1/2	1	1	2	4	**0.133**
Flooding	3	1/3	3	1/2	1	1	2	4	**0.133**
Missing	2	1/3	1/2	1/3	1/2	1/2	1	3	**0.071**
Med.Asst.	1/3	1/4	1/4	1/4	1/4	1/4	1/3	1	**0.033**
Inconsistency									**0.06**

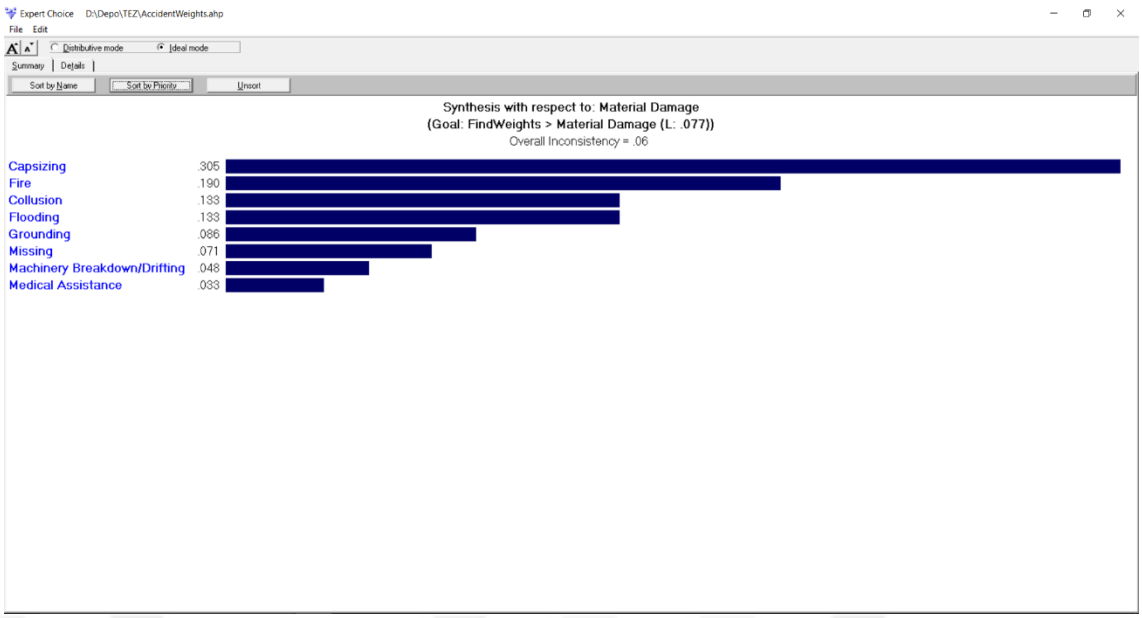

Figure 4.5: Incident type weights in descending order with respect to the "Material Damage" criterion.

Table 4.4: Comparison of alternatives with respect to the "Response Arduousness" criterion.

	Drifting	Capsizing	Grounding	Fire	Collision	Flooding	Missing	Med.Asst.	Relative Imp.
Drifting	1	1/4	1	1/3	1/2	1/2	1/3	2	**0.062**
Capsizing	4	1	4	2	2	3	3	4	**0.276**
Grounding	1	1/4	1	1/3	1/2	1/2	1/2	2	**0.064**
Fire	3	1/2	3	1	2	2	3	3	**0.202**
Collision	2	1/2	2	1/2	1	1	2	2	**0.127**
Flooding	2	1/3	2	1/2	1	1	1/2	2	**0.100**
Missing	3	1/3	2	1/3	1/2	2	1	3	**0.121**
Med.Asst.	1/2	1/4	1/2	1/3	1/2	1/2	1/3	1	**0.048**
Inconsistency									**0.03**

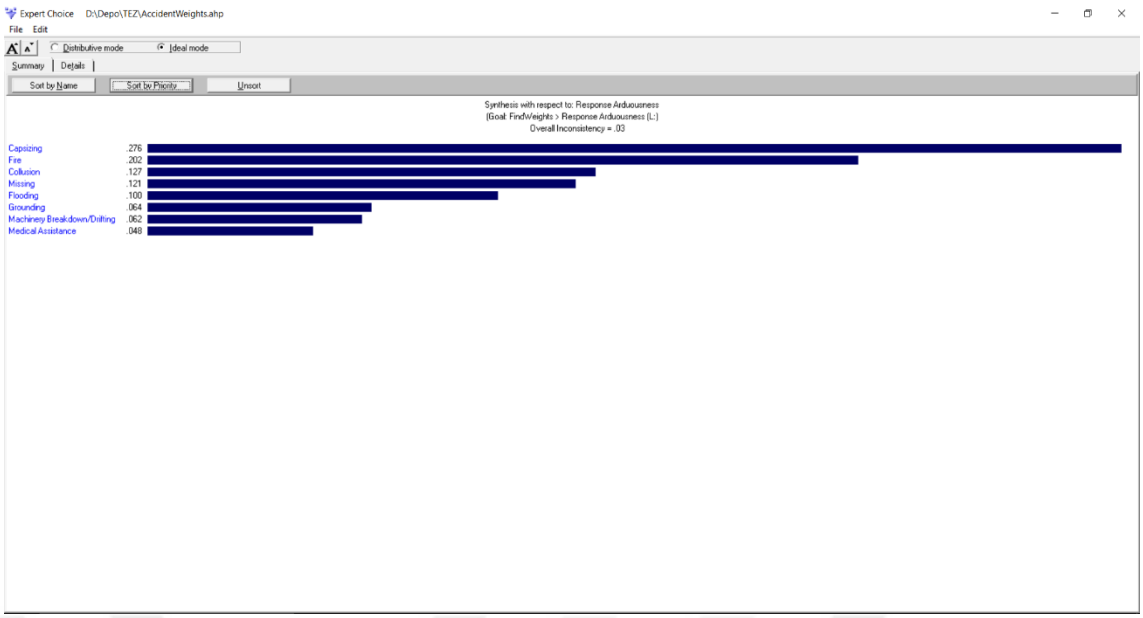

Figure 4.6: Incident type weights in descending order with respect to the "Response Arduousness" criterion.

Table 4.5: Comparison of alternatives with respect to the "Environmental Impact" criterion.

	Drifting	Capsizing	Grounding	Fire	Collision	Flooding	Missing	Med.Asst.	Relative Imp.
Drifting	1	1/4	1/2	1/3	1/3	1/2	1/3	2	**0.053**
Capsizing	4	1	3	2	2	3	2	4	**0.256**
Grounding	2	1/3	1	1/2	1/2	2	1	3	**0.104**
Fire	3	1/2	2	1	1	2	3	4	**0.181**
Collision	3	1/2	2	1	1	3	2	4	**0.178**
Flooding	2	1/3	1/2	1/2	1/3	1	1	3	**0.084**
Missing	3	1/2	1	1/3	1/2	1	1	4	**0.107**
Med.Asst.	1/2	1/4	1/3	1/4	1/4	1/3	1/4	1	**0.037**
Inconsistency									**0.03**

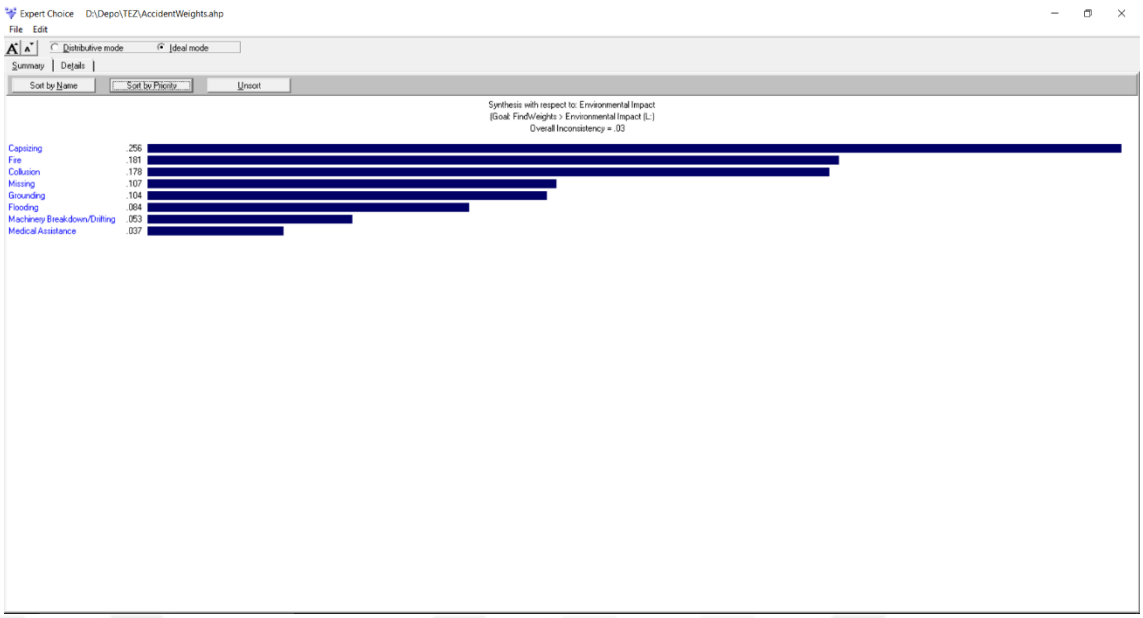

Figure 4.7: Incident type weights in descending order with respect to the "Environmental Impact" criterion.

Finally, we summarized results of the comparison process in Figure 4.8. The first four value sets represent the local weights of eight alternatives for each criterion and the last value set represents final weights. It is clear that capsizing is the dominant incident type in all criteria with a final value of 0.249. Fire follows capsizing with a weight of 0.188 while dominating other types in all criteria. In other words, SAR teams confront with more severe scenes in capsizing and fire incidents than in the others. Collision, missing, medical assistance, flooding, grounding and drifting follow them with the weights of 0.139, 0.119, 0.116, 0.085, 0.060 and 0.044, respectively.

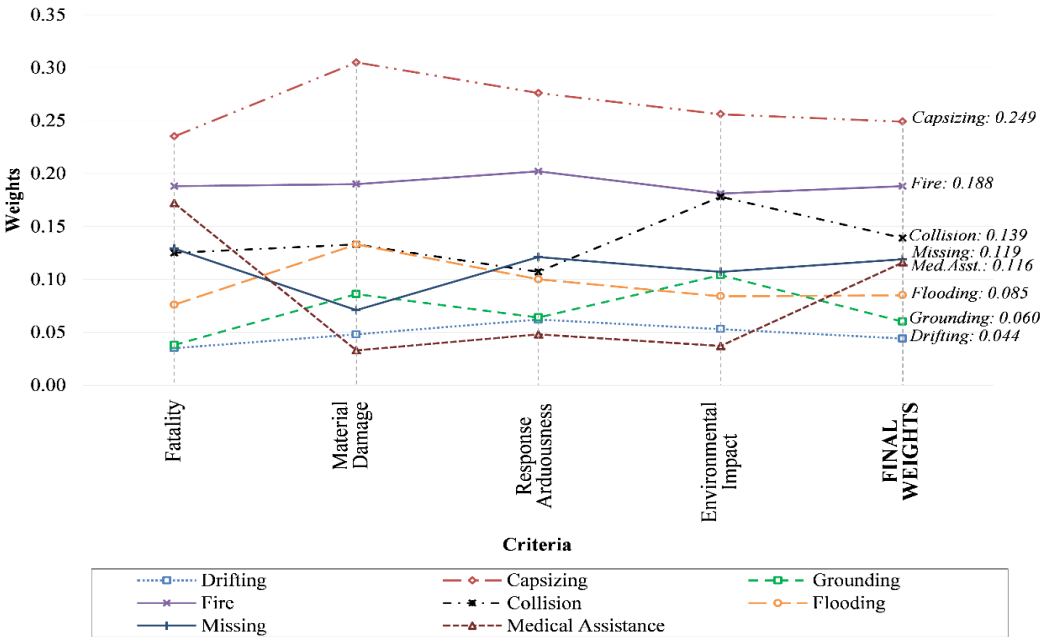

Figure 4.8: Weights of each incident type.

4.1.3 Clustering (Data Aggregation)

We utilized historical incident data with weights obtained from the previous step as the main input data in ZDM. However, we analyzed the input data before utilization and presented a number of key parameters about each incident type in Table 4.6.

Table 4.6: Key parameters of incident data.

Incident Type	Weight (w_i)	Total Number of Incidents Observed	Total Demand (hrs)	Average Demand per Incident (hrs)
Drifting	0.044	474	4032	8.506
Capsizing	0.249	30	2236	74.533
Grounding	0.060	11	79	7.182
Fire	0.188	4	46	11.500
Collision	0.139	2	6	3.000
Flooding	0.085	34	361	10.618
Missing	0.119	43	1072	24.930
Medical Assistance	0.116	118	281	2.381
Total		716	8113	

According to the analysis, SAR teams generally deal with drifting in the area of interest, which was 474 times in the year 2014. Drifting also composes almost a half of total demands with 4032 hours overall. However, capsizing requires the highest operation duration for an incident with 74.5 boat-hours, while collision and medical assistance demand only 3 boat-hour. Additionally, collision and fire are the rarest incident types with 2 and 4 occurrences respectively. Figure 4.9(a) is a plot of incidents having occurred in 2014 along the Aegean Sea sub-responsible region.

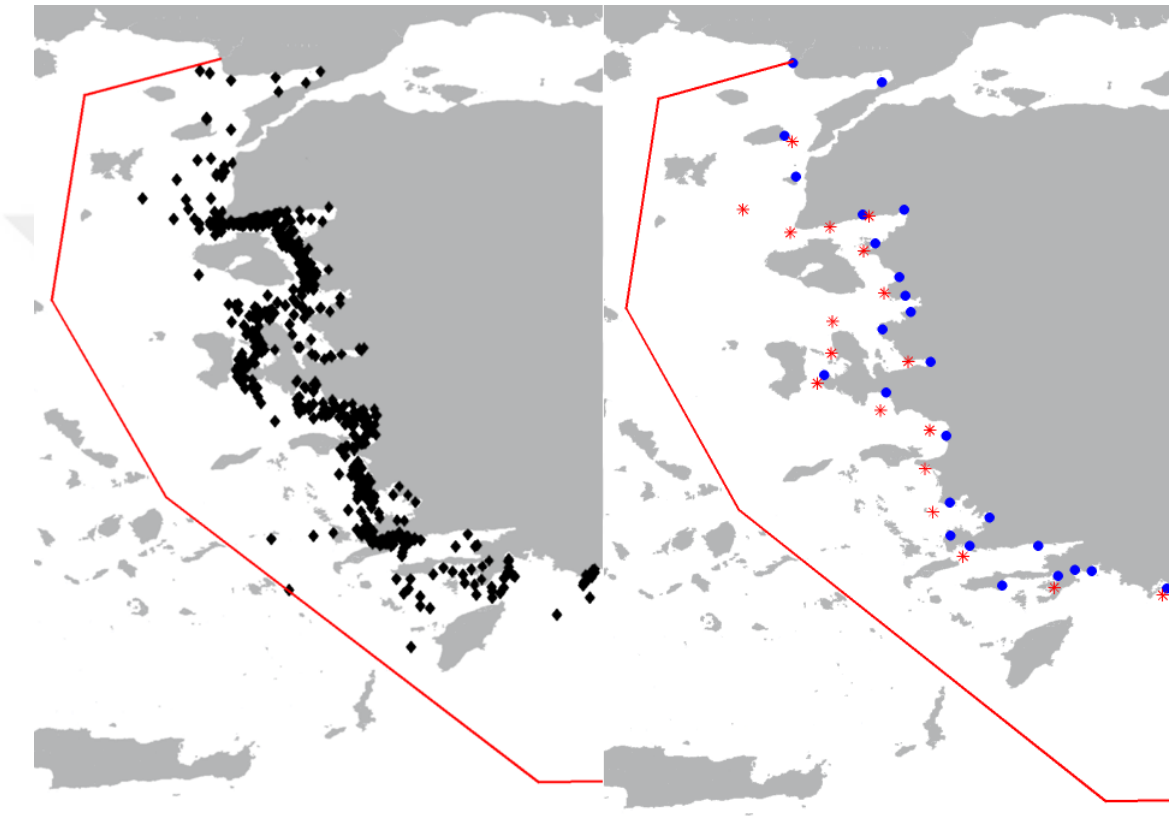

Figure 4.9:(a) Incidents that occurred in 2014 in the Aegean Sea sub-area. Solid line represents the TurCG responsibility zone border. (b) Superincidents (*) determined by ZDM and port locations (●).

After these analyses, we determined $k = \sqrt{716/2} \approx 18$ using *rule of thumb method* and applied *wk*-MCA in MATLAB©. The application provided 18 *superincident* locations with aggregated yearly demand, D_{zi} for incident type $i \in I$ in zone $z \in Z$. Figure 4.9(b) displays 18 *superincident* locations and 25 pre-determined candidate ports. We also summarized the outputs of ZDM in Table 4.7. It gives detailed information about incident types (*i*), total number of

incidents (n_{zi}) and total demands (D_{zi}) of each zone. Furthermore, ZDM outputs prove that data aggregation enables representing dense traffic regions with a generated zone. For example, zone 15 has the highest demand in the area of interest while representing the region between Bodrum and a Greek island, which is popular for cruise tours and water sports. Given as another example, zone 12 is the region between Ayvalik and a Greek island, which is a preferred route for illegal-border crossing activities and has the highest number of incidents observed.

Lastly, we determined distances between maritime incident and ports with the help of an online tool (sea distance calculator in Marine vessel traffic©, www.marinevesseltraffic.com) which calculates the shortest distance between two given locations at sea while considering obstacles such as islands, depths and other geographic features.

Table 4.7: ZDM outputs.

Incident Type		*Superincident Zones*																		
		1	***2***	***3***	***4***	***5***	***6***	***7***	***8***	***9***	***10***	***11***	***12***	***13***	***14***	***15***	***16***	***17***	***18***	**Total**
Drifting	# of incidents	12	39	6	44	35	22	2	43	30	31	27	70	6	9	43	26	25	4	**474**
	Demand (hrs)	65	326	18	322	214	191	18	404	193	281	180	426	37	169	271	520	362	35	**4032**
Capsizing	# of incidents	2	1	1	3	2	2	0	2	1	1	3	1	1	0	9	0	1	0	**30**
	Demand (hrs)	288	5	10	284	120	204	0	95	10	7	393	30	60	0	658	0	72	0	**2236**
Grounding	# of incidents	0	1	0	0	1	0	0	1	2	0	0	0	0	1	4	1	0	0	**11**
	Demand (hrs)	0	8	0	0	17	0	0	6	7	0	0	0	0	3	22	16	0	0	**79**
Fire	# of incidents	1	0	0	0	0	0	0	0	0	1	0	0	0	0	2	0	0	0	**4**
	Demand (hrs)	7	0	0	0	0	0	0	0	0	10	0	0	0	0	29	0	0	0	**46**
Collision	# of incidents	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	**2**
	Demand (hrs)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	2	**6**
Flooding	# of incidents	0	3	0	4	1	3	0	7	2	2	1	6	1	1	2	1	0	0	**34**
	Demand (hrs)	0	19	0	84	3	97	0	60	12	9	8	31	5	6	6	21	0	0	**361**
Missing	# of incidents	4	3	5	1	1	2	0	1	1	3	4	1	2	4	7	1	0	3	**43**
	Demand (hrs)	130	196	15	2	5	104	0	3	238	16	149	24	11	72	94	4	0	9	**1072**
Medical Assistance	# of incidents	12	0	1	4	1	4	3	4	5	1	2	1	1	47	16	0	2	14	**118**
	Demand (hrs)	31	0	2	4	2	7	9	8	10	2	7	3	2	119	30	0	19	26	**281**
TOTAL	# of incidents	31	47	13	56	41	33	5	58	41	39	37	79	11	62	84	29	28	22	**716**
	Demand (hrs)	**521**	**554**	**45**	**696**	**361**	**603**	**27**	**576**	**470**	**325**	**737**	**514**	**115**	**369**	**1114**	**561**	**453**	**72**	**8113**

4.1.4 Optimization Model

Input data of our optimization model could be classified by their relations with incidents and boats. In addition to the incident parameters determined in the previous steps, crt_i is another key parameter which indicates the time threshold for intercepting incident type *i*. Even if it could be different in other SAR organizations,

TurCG aims to respond all incidents within 30 minutes. Thus, we defined critical response time threshold as $crt_i = 0.5$ hours, $\forall i \in I$. Furthermore, response times to incidents in zone *z*, rt_{bpz}, is determined by dividing the distance between port *p* and zone *z* with the operation speed of type *b* boat.

Parameters cf_{bp} , cv_b, S_b , $u_b^{\min}$, $u_b^{\max}$, r_b and γ_b are input data of type *b* boat in our optimization model. cf_b indicates the yearly fixed cost of locating boat type *b* in port *p* and cv_b is the operating cost of type *b* boat for an hour considering maintenance, material and consumption cost. While cf_{bp} and cv_b are about budgetary policy which could be changed in the future, S_b , $u_b^{\min}$, $u_b^{\max}$, r_b and γ_b are about long-standing business and technical policies. S_b, yearly operation capacity of type *b* boat, is a technical parameter and derived from technical documents. However, $u_b^{\min}$, $u_b^{\max}$, r_b and γ_b are about business rules that consider allocation from a strategic perspective. Key parameters of each boat type are shown in Table 4.8. Also, we imported the parameter of port capacities into the model as shown in Table 4-9. Finally, we determined the sclarization coefficient values (θ_1, θ_2 and θ_3) as 15.86x10^{-3}, 448.915x10^{-3} and 0.524x10^{-3} respectively, with Nadir and Utopia point approach.

Table 4.8: Key parameters of type *b* boat.

Boat type	S_b **(hrs)**	**Speed (kts)**	**Range (nm)**	ℓ_b **(mts)**	$u_b^{\min}$ **(units)**	$u_b^{\max}$ **(units)**
B1	1000	22	300	89	1	1
B2	550	27	110	37	1	2
B3	600	27	100	41	1	2
B4	550	27	95	35	1	2
B5	400	18	90	36	1	2
B6	400	45	75	31	1	2
B7	350	47	65	23	1	2
B8	300	62	55	16	1	2
B9	100	54	20	10	2	3

Table 4-9: Port capacities (mts).

Port#	L_b (mts)	Port#	L_b (mts)
P1	120	**P14**	100
P2	90	**P15**	90
P3	150	**P16**	180
P4	100	**P17**	110
P5	120	**P18**	350
P6	150	**P19**	400
P7	100	**P20**	120
P8	300	**P21**	100
P9	350	**P22**	74
P10	110	**P23**	80
P11	400	**P24**	400
P12	95	**P25**	200
P13	150		

4.1.5 Results of the Optimization Model

We used 12 MoEs mentioned in Section 3.2.3 to record optimization model outputs. First, we applied two strategies with objective function weights which could be determined by decision-makers as $\omega_1 = 0.50, \omega_2 = 0.25, \omega_3 = 0.25$ and $\omega_1 = 0.90, \omega_2 = 0.05, \omega_3 = 0.05$. In both strategies, minimizing total weighted delay has more importance than the other two sections of objective function. However, strategy #2 sets importance on minimizing the total delay 18 times higher than on budgetary and supply while strategy #1 provides a nearly balanced approach towards

objective function sections.

Table 4.10: Results of the optimization model.

MoE#	Definition	Formula	Strategy-1 $\omega_1 = 0.50$ $\omega_2 = 0.25$ $\omega_3 = 0.25$	Strategy-2 $\omega_1 = 0.90$ $\omega_2 = 0.05$ $\omega_3 = 0.05$
MoE_1	Total delay (hrs)	$\sum_{b\in B}\sum_{p\in P}\sum_{z\in Z}\sum_{i\in I} n_{zi} dev_{bpzi}^{crt+}$	7.755	2.143
MoE_2	Total weighted delay (hrs)	$\sum_{b\in B}\sum_{p\in P}\sum_{z\in Z}\sum_{i\in I} w_i n_{zi} dev_{bpzi}^{crt+}$	1.047	0.380
MoE_3	Shortage on the budget (M$)	dev^{fb+}	0	0
MoE_4	Ratio of the budget used (%)	$\frac{FB + dev^{fb+} - dev^{fb-}}{FB}$	93%	94%
MoE_5	Total excess of AOC (hrs)	$\sum_{b\in B}\sum_{p\in P} dev_{bp}^{s-}$	20	224
MoE_6	Total shortage on the AOC (hrs)	$\sum_{b\in B}\sum_{p\in P} dev_{bp}^{s+}$	0	39
MoE_7	Total deviation on the AOC (hrs)	$\sum_{b\in B}\sum_{p\in P} dev_{bp}^{s-} + dev_{bp}^{s+}$	20	263
MoE_8	Ratio of the utilized fleet size (%)	$\frac{\sum_{b\in B}\sum_{p\in P} x_{bp}}{\sum_{b\in B} U_b}$	90%	92%
MoE_9	Ratio of the incidents intercepted (%)	$\frac{\sum_{k\in K_i}\left[1-\prod_{b\in B}\prod_{p\in P}\prod_{z\in Z}\prod_{i\in I}\left(1-\lambda_{bpzi}\right)\right]}{\sum_{z\in Z}\sum_{i\in I} n_{zi}}$	100%	100%

Table 4.10(Continue)

MoE#	Definition	Formula	Strategy-1 $\omega_1 = 0.50$ $\omega_2 = 0.25$ $\omega_3 = 0.25$	Strategy-2 $\omega_1 = 0.90$ $\omega_2 = 0.05$ $\omega_3 = 0.05$
MoE_{10}	Ratio of the demand satisfied (%)	$\frac{\sum_{k \in K_i} t_k \left[1 - \prod_{b \in B} \prod_{p \in P} \prod_{z \in Z} \prod_{i \in I} \left(1 - \lambda_{bpzi} \right) \right]}{\sum_{z \in Z} \sum_{i \in I} D_{zi}}$	100%	100%
MoE_{11}	Total reaction time (hrs)	$\sum_{b \in B} \sum_{p \in P} \sum_{z \in Z} \sum_{i \in I} rt_{bpz} \lambda_{bpzi}$	393.502	302.532
MoE_{12}	Reaction time per incident (hrs)	$\frac{\sum_{b \in B} \sum_{p \in P} \sum_{z \in Z} \sum_{i \in I} rt_{bpz} \lambda_{bpzi}}{\sum_{z \in Z} \sum_{i \in I} n_{zi}}$	0.549	0.423

The analysis of results shows that increment on ω_1 causes a significant decrease in total delay over critical response times, being/dropping from 7.755 to 2.143. However, strategy #2 requires 1% more budget and expands the fleet size by 2% while improving delay times of strategy #1. Strategy #1 ends up with little deviation; on the contrary, strategy #2 results in a total of 263 hours supply deviation. Besides, reaction times per incident in strategy #2 is under critical response time threshold $crt_i = 0.5, \forall i \in I$, total delay, though, is 2.143 hours. It could be explained by the fact that incidents intercepted within critical time threshold have low response times and these values keep "reaction time per incident" under threshold (0.5 hour) whereas there are a number of incidents responded lately.

4.1.6 Sensitivity Analysis

In the previous step, we applied two strategies that mainly consider minimizing the total response time over critical time threshold. However, decision-makers could have distinct priorities during the allocation process and apply different weights in the objective function. For example, a SAR organization could have strict business rules about the management of boat capacities and decision-makers set the weights

about capacity deviation (ω_3) high. Therefore, as a sensitivity analysis, we decided to solve the model with a number of notable strategies. Besides the evaluation of the model's flexibility, the analysis also helps decision makers to observe the trade-offs in different prioritization and weighting strategies. We assumed that minimizing the total delay should be the main goal and it should have higher weights; indeed, we tried to test our model with all possible weighting scenarios. We applied 15 strategies and compared them with respect to the values of each objective function section (MoE_1 to MoE_8) shown in Table 4.11.

Table 4.11:Sensitivity analysis with different weighting strategies.

Strategy #	Objective Function Component Weights			Total Delay (hrs)	Total Weighted Delay (hrs)	Shortage on budget (M$)	Budget Used (%)	Total excess of AOC (hrs)	Total shortage on the AOC (hrs)	Total deviation on the AOC (hrs)	Utilized Fleet Size (%)
	ω_1	ω_2	ω_3	MoE_1	MoE_2	MoE_3	MoE_4	MoE_5	MoE_6	MoE_7	MoE_8
1	0	0.50	0.50	456.766	33.302	0	93	14	0	14	96
2	0.10	0.75	0.15	9.512	1.097	0	89	13	0	13	95
3	0.10	0.45	0.45	9.080	1.089	0	91	20	0	20	95
4	0.20	0.75	0.05	9.121	1.058	0	88	120	0	120	94
5	0.33	0.33	0.33	8.718	1.022	0	90	13	0	13	92
6	0.40	0.35	0.25	9.080	1.089	0	90	13	0	13	92
7	0.45	0.45	0.10	7.200	1.081	0	90	8	0	8	90
8	0.50	0.25	0.25	7.755	1.047	0	93	20	0	20	90
9	0.60	0.20	0.20	7.230	0.978	0	93	22	0	22	90
10	0.70	0.20	0.10	6.512	0.915	0	93	28	0	28	90
11	0.80	0.15	0.05	3.511	0.421	0	93	221	29	250	91
12	0.90	0.05	0.05	2.143	0.380	0	94	224	39	263	92
13	0.95	0.040	0.01	0.140	0.011	0	94	587	340	927	94
14	0.99	0.005	0.005	0.140	0.011	0	94	571	330	901	96
15	1	0	0	0.056	0.003	0	94	1017	890	1907	96

Firstly, results show that the planned budget is enough to implement all strategies. The model utilizes 94% of the planned budget even though decision-makers unbound "shortage on budget" with a value of $\omega_2 = 0$ in strategy #15. Secondly, the model provides at least 4% saving in the fleet size as can be seen in strategies #1, 14 and 15. Thirdly, the analysis displays that the model does not ensure responding all incidents within the critical time threshold even if budget and supply capacities are unbounded. In strategy #15, the model utilizes 96% of the fleet size with a total of 1907-hour supply deviation; nevertheless, it reaches the minimum total delay of 0.056 hours. Finally, equal weights are applied in strategy #5 and the model provides better

solutions than in strategies #1, 2, 3, 4 and 6 in terms of objective functions sections which are represented by MoE_2, MoE_3 and MoE_7.

In Figure 4.10, we intend to display the trade-offs in total weighted delay (MoE_2), percentage of the budget used(MoE_4), total deviation on the AOC (MoE_7) and percentage of the fleet utilized (MoE_8) for all strategies. In the graph, we used two vertical axes since the value of each MoE have a different scale. Parameters of the budget used and utilized fleet size parameters use the left vertical axis. Total weighted delay and total deviation on the AOC use the right vertical axis which has logarithmic scale. It shows that total delay decreases considerably with the help of the increment in fleet size and supply deviation.

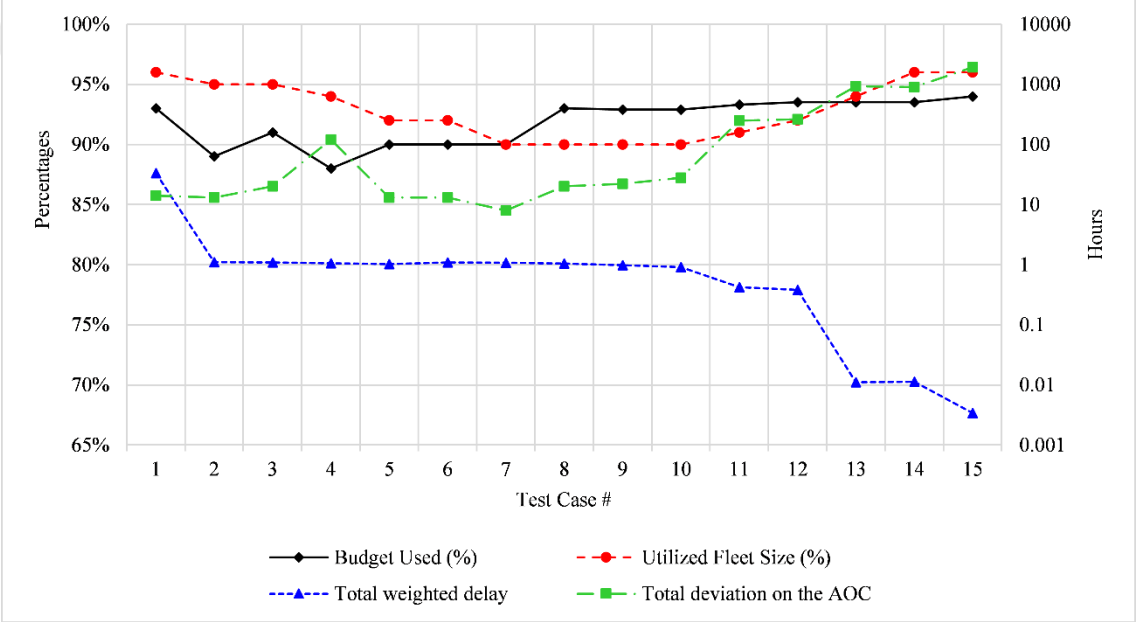

Figure 4.10: Total weighted delay (MoE_2), percentage of the budget used (MoE_4), total deviation on the AOC (MoE_7) and percentage of the utilized fleet (MoE_8) values for each strategy.

4.2 SIMULATION MODEL

4.2.1 Inputs

We used the allocation plan obtained from strategy #12 ($\omega_1 = 0.90, \omega_2 = 0.05, \omega_3 = 0.05$) as our input in the simulation model. In strategy #12, optimization model activates 13 ports and utilizes 8 different boat types as shown in Table 4.12.

Table 4.12: Allocation plan of strategy #12.

	P3	P4	P5	P6	P7	P9	P11	P13	P14	P16	P19	P22	P25
B1	-	-	-	-	-	-	-	-	-	-	-	-	-
B2	-	-	-	-	1	-	-	-	-	-	-	-	-
B3	-	-	-	-	-	1	-	1	-	-	1	-	-
B4	-	-	1	1	-	-	-	-	-	-	-	-	-
B5	-	-	-	-	-	-	-	-	1	1	1	-	-
B6	-	1	1	-	-	-	1	-	-	-	-	-	-
B7	-	-	-	-	-	1	-	1	-	1	-	-	-
B8	-	1	-	-	-	-	-	-	-	1	-	1	1
B9	2	-	-	-	-	-	-	2	2	-	-	2	-

To generate incident input data, we divided the area of interest, The Aegean Sea sub-responsible region, into 0.25x0.25 degree-sized grids with respect to incident density. Figure 4.11(a) displays all incidents having occurred in the Aegean Sea sub-responsible region throughout and Figure 4.11(b) shows the generated grid structure of the area of interest.

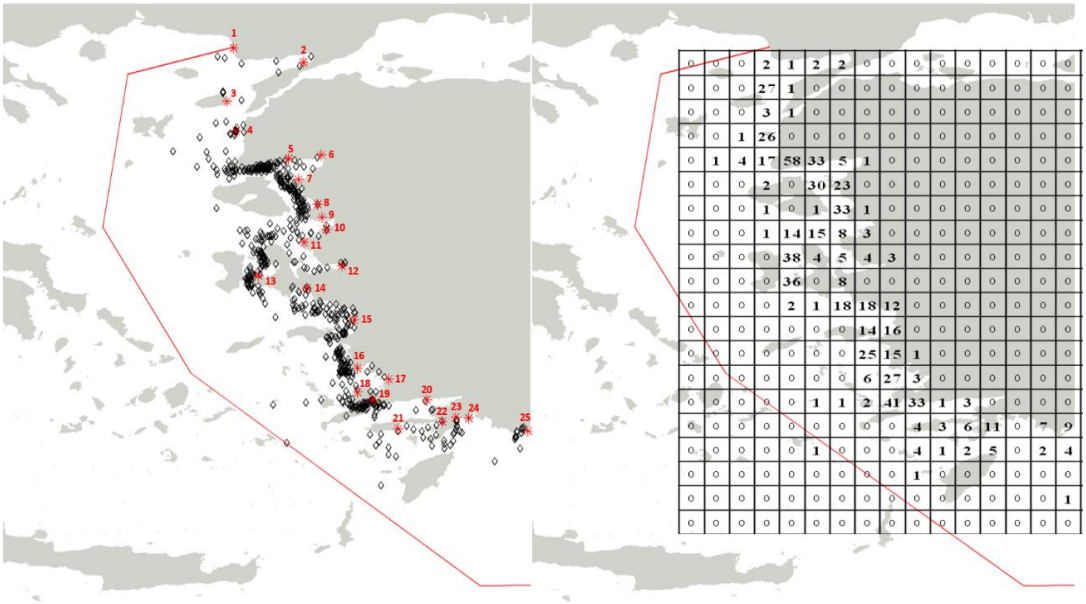

Figure 4.11: (a) Incidents (◊) and ports (*). Solid line represents the TurCG responsibility zone border. (b) Grid structure of sub-responsible region.

In grid view structure, we confronted with 71 regions where at least one incident was observed. Then, we assumed that incidents occurred at the center of each grid and computed 71x13 grid-port maritime distances matrix. The number of incidents taking place in each grid is used to determine the incident inter-arrival time. Besides, incident type breakdowns of each grid were utilized to determine the type of generated incidents. Applying this approach, we tried to reflect incident characteristics of sub-regions via grid structure. We analyzed all incidents in terms of demand size and showed time density in Figure 4.12. The analysis showed that distribution of operation times fit in the geometric distribution with parameter (φ *=0.00147).* Consequently, we utilized the allocation plan obtained from strategy #12 to supply stochastic demands that were generated in a grid for evaluating the performance of optimization model.

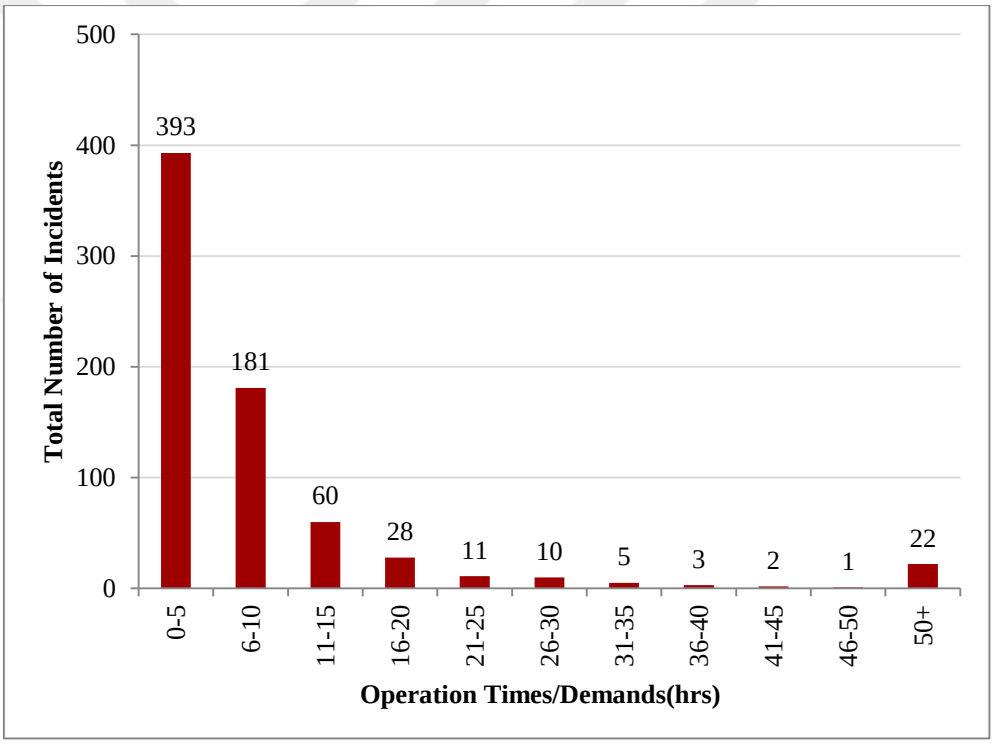

Figure 4.12: Operation time density.

4.2.2 Simulation Models

To evaluate the optimization model properly, we demonstrated two distinctive simulation models: model with grids (SimModel-1), model with data aggregation (SimModel-2). In both models, we followed four different business rules about supply capacity policy. Firstly, we ran the model with the business rule that does not

allow decision-makers to use boats having already consumed all of the yearly supply capacity (AOC). It was followed by three alternative business rules that allow 10%, 20% and unlimited exceedance on the AOC. All simulation runs were conducted in Micro Saint Sharp© version 3.7.

The structure of SimModel-1 is shown in Figure 4.13. Each grid is represented by 71 task modules on the left side of the figure. Incident entity that is generated in a grid takes a step forward and enters into the "Center" task module. In the "Center", the model tries to determine port and boat assignments and sends incident entity to the determined port task. However, in case of no idle boat, incident entity lines up in the queue (FIFO) in "Waiting" task module to wait for an idle capable boat. Port modules represent the proceeding process to incident locations. Then, incident entity follows the path to "Operation#" task where SAR operation is conducted. Finally, task groups on the right side of the figure release boats which complete the duty and collects all related data.

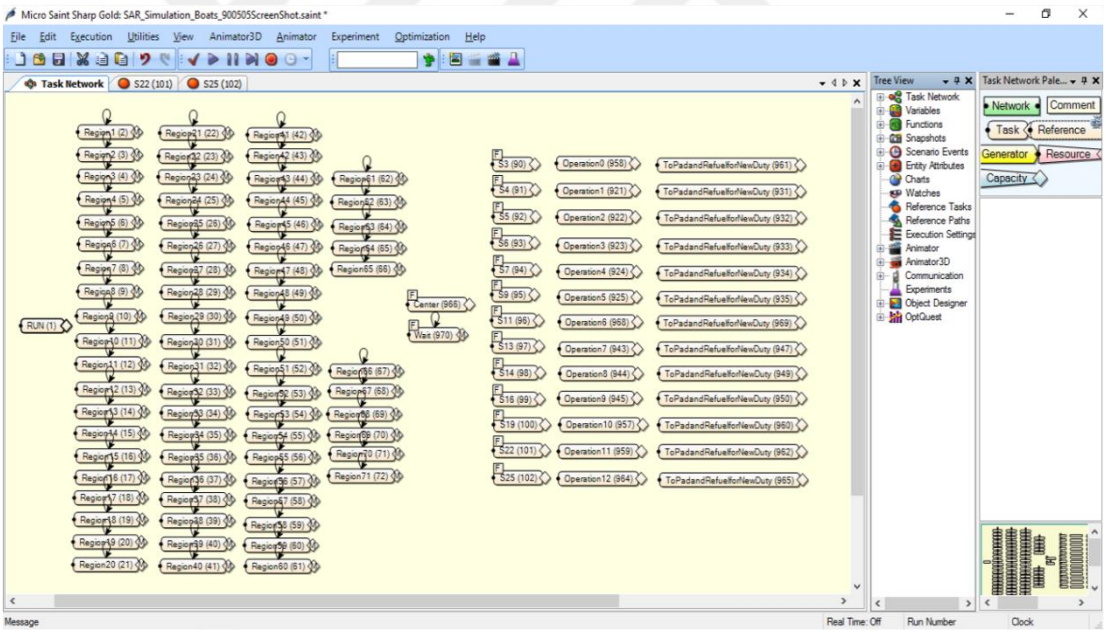

Figure 4.13: Simulation model structure of SimModel-1 in Micro Saint Sharp©.

In SimModel-2, we utilized 18 zones obtained from data aggregation (ZDM) to represent regions in which incidents occur. Except this difference, we formulated SimModel-2 with the same assumptions and business rules implemented in SimModel-1. The structure of SimModel-2 is shown in Figure 4.14.

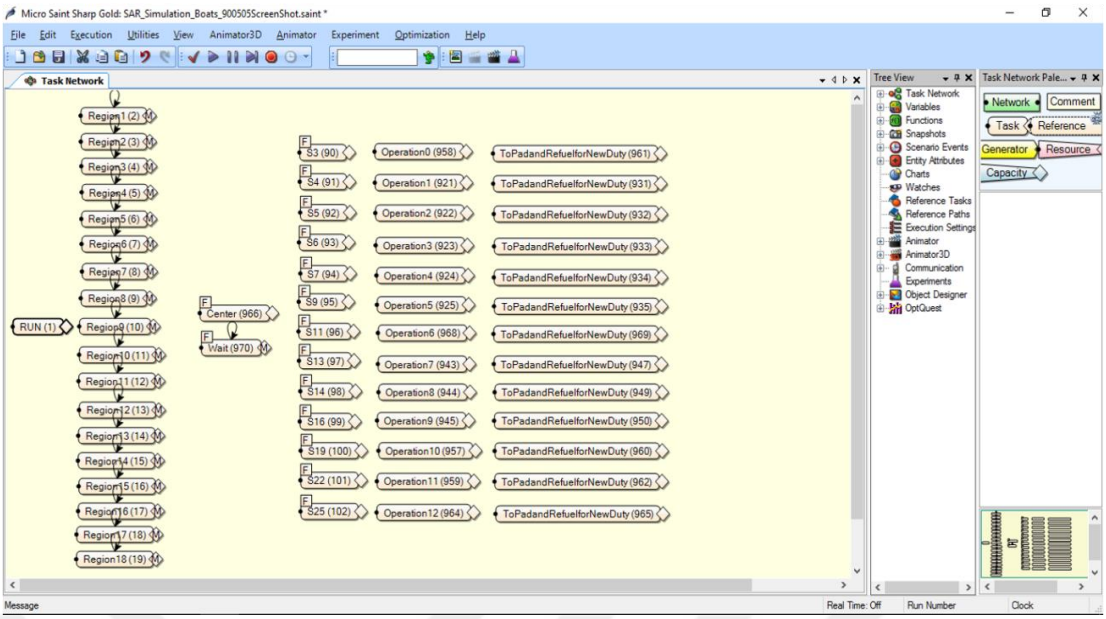

Figure 4.14: Structure of the SimModel-2 in Micro Saint Sharp©.

4.2.3 Results of Simulation Model

Simulation models were performed 250 times for each business rule and selection criteria. Table 4.13 displays results of both optimization model and simulation model with grids (SimModel-1).

Table 4.13: Results of optimization model and SimModel-1

MoE#	Definition	Opt. Model Result	Simulation Model Results							
			Case-I: Shortage on the AOC 0%		Case-II: Shortage on the AOC 10%		Case-III: Shortage on the AOC 20%		Case-IV: Shortage on the AOC Unlimited	
			Remaining Capacity	Speed	Remaining Capacity	Speed	Remaining Capacity	Speed	Remaining Capacity	Speed
MoE_1	Total delay (hrs)	2.143	193.69	224.146	170.06	189.204	141.438	140.129	79.384	42.69
MoE_2	Total weighted delay (hrs)	0.38	14.607	16.046	12.754	13.933	10.72	10.497	6.165	3.47
MoE_3	Shortage on the budget (M$)	0	0	0	0	0	0	0	0	0

Table 4.13 (Continue)

MoE#	Definition	Opt. Model Result	Simulation Model Results							
			Case-I: Shortage on the AOC 0%		Case-II: Shortage on the AOC 10%		Case-III: Shortage on the AOC 20%		Case-IV: Shortage on the AOC Unlimited	
			Remaining Capacity	Speed	Remaining Capacity	Speed	Remaining Capacity	Speed	Remaining Capacity	Speed
MoE_4	Ratio of the budget used (%)	94.00%	93.07%	93.30%	94.09%	94.17%	94.83%	94.46%	94.78%	91.99%
MoE_5	Total excess of AOC (hrs)	224	693	612	914	983	1231	1598	2331	4680
MoE_6	Total shortage on the AOC (hrs)	39	154	183	624	692	1118	1311	2082	4016
MoE_7	Total deviation on the AOC (hrs)	263	847	795	1538	1675	2349	2909	4413	8696
MoE_8	Ratio of the utilized fleet size (%)	92.00%	92.00%	92.00%	92.00%	92.00%	92.00%	92.00%	92.00%	92.00%
MoE_9	Ratio of incidents intercepted (%)	100%	92.38%	93.35%	95.84%	96.54%	98.89%	98.89%	99.86%	99.86%
MoE_{10}	Ratio of demands satisfied (%)	100%	92.36%	93.43%	95.96%	96.72%	98.98%	98.95%	99.94%	99.94%
MoE_{11}	Total reaction time(hrs)	302.532	438.89	470.442	422.259	440.418	397.722	391.159	321.743	256.247
MoE_{12}	Reaction time per incident(hrs)	0.422531	0.6580	0.6980	0.6102	0.6319	0.5570	0.5478	0.4462	0.3554

Firstly, results show that both optimization model and SimModel-1 provide no risk in budget. As we apply the allocation plan of analytic approach in simulation models, ratio of utilized fleet (MoE_8) values and surely fixed costs are equal for each experiment. SimModel-1 uses 94.83% of the budget at most whereas assigned boats exceed total of 1118 hours in the AOC. Secondly, in the case where AOC exceedance is not allowed (optimization model assumption), there is difference between analytic and SimModel-1 in terms of total delay (MoE_1) gets its highest value. The optimization model provides 2.143 hours of total delay whereas SimModel-1 results in 193.69 and 224.146 hours of total delay. Besides, reaction time per incident (MoE_{12}) increases by 55.7% even if 7.62% of incidents are not responded (MoE_9). Particularly, 0.658 hours of reaction time per incident (MoE_{12}) indicates that SAR boats are getting late to each incident about 9 minutes in SimModel-1.

With the other three alternative business rules, SimModel-1 provides better solutions in terms of MoE_1, MoE_9, MoE_{10}, MoE_{11} and MoE_{12}. However, ratio of the budget used (MoE_4) worsens especially when "Remaining Capacity" criterion is implemented. As stated in Table 4.8, larger-capacitated units have a higher variable cost than smaller-faster ones. Thus, SimModel-1 is to bear a higher cost when the "Remaining Capacity" criterion is applied. In the case where 10% exceedance on the AOC is allowed, total delay (MoE_1) decreases by 15.6% and boats respond to each incident almost 4 minutes earlier (MoE_{12}). Besides, exceedance on supply capacity provides 3.5% more incidents to be intercepted.

In the case that permits 20% exceedance on the AOC, boats respond to almost %98.9 of stochastically generated incidents while 2349 and 2909 hours of deviation on the AOC occurs. The model provides 25.9% improvement on total delay (MoE_1) when the "Speed" criterion is implemented. Besides, reaction time per incident (MoE_{12}) decreases to 33 minutes.

In the last case that allows full relaxation on capacity policy, SimModel-1 with "Speed" criterion dominates the model with "Remaining Capacity" in all MoE values except MoE_5, MoE_6 and MoE_7. The model provides this dominance along with a %3 lower budget. Outputs of this experiment indicate that we can have at least 42.69 hours of total delay(MoE_1), even though we utilize uncapacitated boats in the model. However, the model provides 0.3554 hours of reaction time per incident (MoE_{12}),

which means responding to each incident in almost 21 minutes.

To sum up, the first three business rules (cases) in SimModel-1 yields higher values for the reaction time per incident (MoE_{12}) when compared with the optimization model. As we relax the capacity policy, total delay (MoE_1), ratio of incidents intercepted (MoE_9) and response time per incident (MoE_{12}) values decrease drastically and align with the analytic solution. For the last business rule (unlimited capacity), SimModel-1 provides the best values for all MoEs with the maximum deviation on the AOC. In order to summarize the scene, we displayed response time of each incident in Figure 4.15 and Figure 4.16.

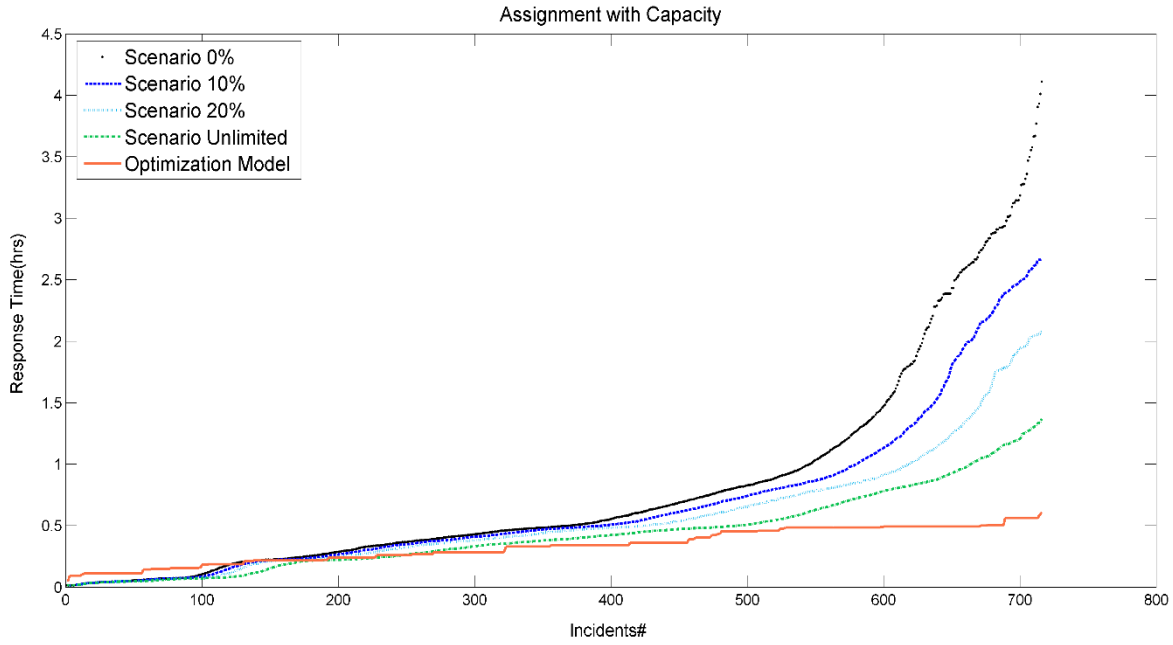

Figure 4.15: Response time of each incident with "Remaining Capacity" (SimModel-1).

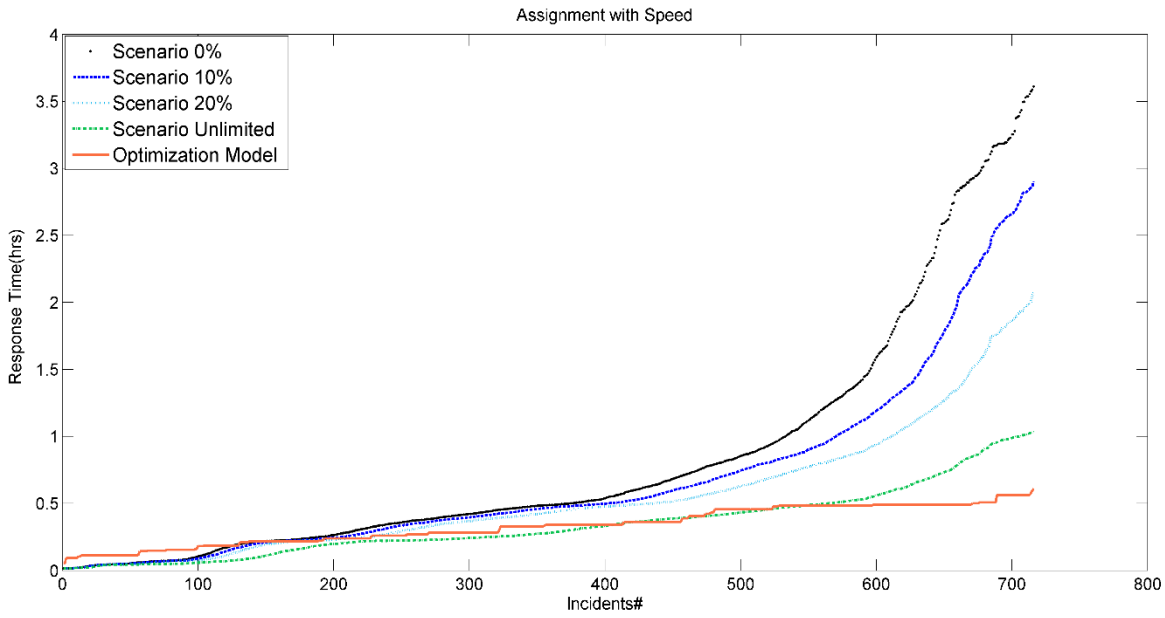

Figure 4.16: Response time of each incident with "Speed" (SimModel-1).

In Table 4.14, we presented the results of SimModel-2 which is demonstrated with data aggregation (ZDM) technique.

Table 4.14: Results of optimization model and SimModel-2.

MoE#	Definition	Opt. Model Results	Simulation Model Results							
			Case-I: Shortage on the AOC 0%		Case-II: Shortage on the AOC 10%		Case-III: Shortage on the AOC 20%		Case-IV: Shortage on the AOC Unlimited	
			Remaining Capacity	Speed	Remaining Capacity	Speed	Remaining Capacity	Speed	Remaining Capacity	Speed
MoE_1	Total delay (hrs)	2.143	97.45	128.278	58.99	89.457	53.485	58.88	26.01	9.119
MoE_2	Total weighted delay (hrs)	0.38	6.33	8.338	4.16	6.147	3.782	4.184	1.99	0.889
MoE_3	Shortage on the budget (M$)	0	0	0	0	0	0	0	0	0
MoE_4	Ratio of the budget used (%)	94.00%	93.07%	93.12%	94.41%	93.80%	94.30%	93.89%	94.23%	91.50%

Table4.14 (Continue)

MoE#	Definition	Opt. Model Results	Simulation Model Results							
			Case-I: Shortage on the AOC 0%		Case-II: Shortage on the AOC 10%		Case-III: Shortage on the AOC 20%		Case-IV: Shortage on the AOC Unlimited	
			Remaining Capacity	Speed	Remaining Capacity	Speed	Remaining Capacity	Speed	Remaining Capacity	Speed
MoE_5	Total excess on the AOC (hrs)	224	891	967	1203	1506	1245	1910	1412	4157
MoE_6	Total shortage on the AOC (hrs)	39	158	204	680	695	718	1056	900	3201
MoE_7	Total deviation on the AOC (hrs)	263	1049	1171	1883	2201	1963	2966	2312	7358
MoE_8	Ratio of utilized fleet size (%)	92.00%	92.00%	92.00%	92.00%	92.00%	92.00%	92.00%	92.00%	92.00%
MoE_9	Ratio of the incidents intercepted (%)	100%	94.18%	94.46%	98.61%	97.51%	98.89%	98.48%	100.00%	100.00%
MoE_{10}	Ratio of demands satisfied (%)	100%	93.96%	94.38%	98.41%	97.33%	98.82%	98.44%	99.86%	99.86%
MoE_{11}	Total reaction time(hrs)	302.532	325.73	353.666	295.84	317.424	289.287	284.536	260.39	208.853
MoE_{12}	Reaction time per incident(hrs)	0.422531	0.4790	0.5186	0.4155	0.4509	0.4052	0.4002	0.3607	0.2893

Before we discuss results of all cases individually, there are a number of general points that should be mentioned about simulation model outputs. Firstly, “Speed” criterion in Case-IV is the dominant experiment over all tests in terms of all MoEs (except MoE_7). However, for other cases, the model with “Speed” criterion provides

worse values in total delay (MoE_1) and total deviation on the AOC (MoE_7). Secondly, the model provides reaction time per incident (MoE_{12}) value under the critical time threshold (0.5 hour) in all cases (except the first case with "Speed" criterion). Finally, as in SimModel-1, implemented budget is enough to conduct each business rule and the model spends 0.41% more funds than the optimization model does at most.

In the first case, SimModel-2 is far worse than the optimization model in terms of total delay (MoE_1), even though there is not much difference in the other MoEs. While the total delay in optimization model is 2.143 hours, boats respond to incidents with 97.45 and 128.278 hours of total delay (MoE_1) in SimModel-2. SimModel-2 also provides five times higher exceedance on the AOC (MoE_6) than the optimization model does. Even if 158 and 204 hours of exceedance occurs on the AOC, approximately 5.5% of generated incidents cannot be responded by any capable boat. For intercepted incidents, mean time to be responded is about 28.75 minutes (Remaining Capacity) and 31.11 minutes (Speed). In addition, SimModel-2 utilizes 1% lower budget than the analytic approach does.

SimModel-2 improves the delay time about 40%(Remaining Capacity) and 30%(Speed) when 10% exceedance is allowed on the AOC. With this relaxation, total exceedance (MoE_6) jumps from 158 and 204 hours to 680 and 695 hours. Moreover, ratio of incidents intercepted (MoE_9) increases by 4% and reaction time per incident (MoE_{12}) decreases by 13% to 24.9 and 27 minutes. Along with these improvements, ratio of the budget used (MoE_4) worsens about 1%.

When relaxation on the AOC is expanded to 20% (Case-III), we confront with a different improvement ratio for each selection criterion. Total delay (MoE_1) decreases by 35% with the "Speed" criterion while it is by 10% with that of "Remaining Capacity". This difference also appears in the reaction time per incident (MoE_{12}). While boats respond to incidents 0.6 minutes earlier with the "Remaining Capacity" criterion, reaction time per incident (MoE_{12}) decreases to 24 minutes in the other criterion.

In the last case, the most important point is to mention the ratio of incidents intercepted (MoE_9). While SimModel-2 cannot provide full coverage in other cases, it responds to all generated incidents in Case-IV. Total delay (MoE_1) also gets the

lowest value of 9.119 hours with the “Speed” criterion whereas reaction time per incident decreases to 17.3 minutes. Furthermore, SimModel-2 utilizes 2.5% lower budget than the optimization model itself, with that, boats exploit the highest exceedance on the AOC with 3201 hours.

We plotted the response time of each incident in Figure 4.17 and Figure 4.18 in order to visualize the dominance of any cases in terms of that factor.

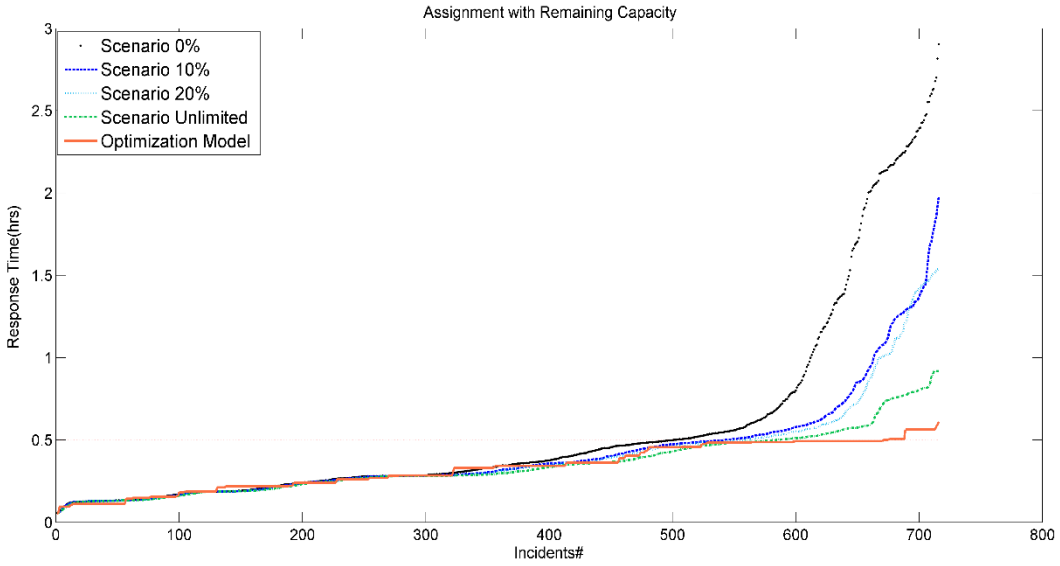

Figure 4.17: Response time of each incident with “Remaining Capacity” (SimModel-2).

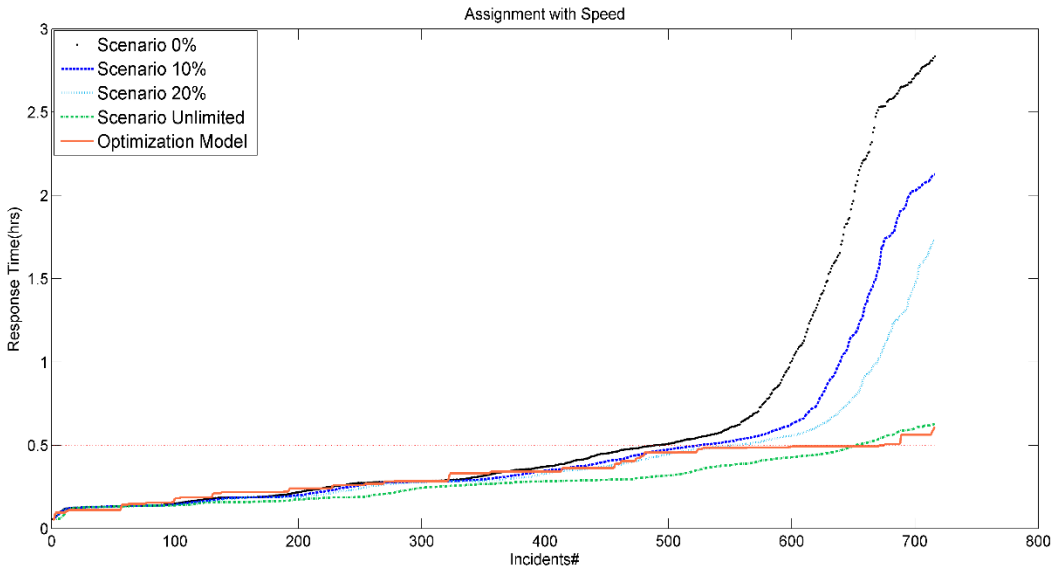

Figure 4.18: Response time of each incident with "Speed" (SimModel-2).

5 DISCUSSION

In literature, we confront with few studies addressing locating maritime SAR resources mentioned in Section 2.1. Even though each study tries to solve the problem from a different perspective, there are a number of common approaches applied in formulation:

(1) Authors focus mainly on cost minimization and coverage. In contrast with private services, user accessibility and response time should be the main concern in public and emergency services. (Balcik and Beamon, 2008, p.101-121).

(2) Demand is aggregated in each station and identified as the *station's demand*. Then, models try to meet that demand with the total capacity of boats allocated at the station. However, this approach does not consider actual locations of the demand which affect the allocation plan in terms of response time.

(3) Models do not consider the severity of each incident type.

(4) Technical limitations on resources and strategic business rules are not considered in detail.

In this thesis, we encompass important aspects of these studies along with the weaknesses above and develop a two-stage methodology. In first stage, we propose a facility location model with multiple objectives for the case of maritime SAR boats. We consider several different criteria in our model, incorporated into the objective function and constraints. There are three objectives that are weighted in a single linear objective function. Total weighted delay, deviation from fleet operating cost and deviation of resources' workload from their operation capacity are minimized. Historical incidents are used in the study and assessed based on several factors representing the incidents' severity to assign a weight to each incident type. AHP method is used to calculate incident weights. Then, historical incidents are aggregated into clusters through a Zonal Distribution Model in order to simplify the calculation process. Finally, the multi-objective mathematical model is developed to find the optimal location and allocation of SAR resources. Business rules and capability constraints are considered in the model.

At first, we solved the model for two weighting strategies ($\omega_1 = 0.50, \omega_2 = 0.25, \omega_3 = 0.25$ and $\omega_1 = 0.90, \omega_2 = 0.05, \omega_3 = 0.05$). Then, 13 more strategies were conducted to perform a sensitivity analysis of the model. The model is constructed as an ILP and solved by CPLEX. Thus, it is clear that all results are optimum.

Results show that boats can respond to almost all incidents within the critical time threshold (0.5 hour/30 minutes), if we lead our all effort to minimizing total delay in strategy #15 ($\omega_1 = 1, \omega_2 = 0, \omega_3 = 0$) which results in only a total of 0.056 hour (3 minutes) delay in 716 operations (which can be neglected by a decision-maker). The model also does not utilize 4% of all available fleet when there is no restriction on budget and capacity deviation.

The highest value of total delay (456.766 hours) is obtained in strategy #1 where $\omega_1 = 0.$ Slightly increasing the weight to $\omega_1 = 0.1$ leads to a severe change in total delay (9.119 hours). In Figure 4.10, it can be clearly seen that total delay (MoE_1) decreases drastically when both utilized fleet size and capacity deviation increase. As total delay(MoE_1), total deviation on the AOC (MoE_7) reaches the highest value, 1907 hours, in strategy #15. Although 890 hours of total deviation on the AOC increases the variable cost (cv_b), the model does not confront with a budgetary risk and utilizes 94% of the annual budget at most.

The analysis also shows that strategy #5 dominates strategies #1, 2, 3, 4 and 6 in terms of objective function sections which are represented by MoE_2, MoE_3 and MoE_7. Hence, it makes sense to assign weights as $\omega_1 > \omega_2, \omega_3$, in accordance with the decision-makers' views.

We select strategy #12 ($\omega_1 = 0.90, \omega_2 = 0.05, \omega_3 = 0.05$), of which outputs are detailed in Table 4.10, to evaluate the performance of analytic solution in our simulation model at stage-2. We develop two simulation models, namely SimModel-1 and SimModel-2, using the allocation plan of optimization model as inputs. The main difference between two models is that, in SimModel-1, the area of interest is partitioned into 0.25x025 degree-sized grids to generate stochastic demand along with historical incident data. In SimModel-2, we utilize 18 *superincident* zones that are obtained from data aggregation technique mentioned in Section 4.1.3.

Besides, for each simulation model, two different selection criteria, “Remaining Capacity” and “Speed”, are applied to select the boat in cases when there is more than one idle boat available. Also, four cases about capacity policy are performed in each simulation model and results are shown in Table 4.13 and Table 4.14.

When we compare results of simulation models with the optimization model, we notice that there is a significant difference in terms of total delay (MoE_1). However, with the capacity relaxation (Case-II, Case-III and Case-IV), MoE_1, MoE_{11} and MoE_{12} improves and the value of total delay (MoE_1) starts getting closer to output of optimization model.

Making use of the “Remaining Capacity” selection criterion, the operation center assigns the boat with more available capacity in case of an incident and maintains balanced workload at a port. As high-capacity units are slower, the operation center begins operations with slower units and utilizes them till their capacity gets equal with the faster ones. This approach provides better solutions than other selection criterion when limited capacity policy is conducted (Case-I and Case-II). However, results of this criterion worsen when boat capacities are unbounded.

SimModel-1 gives the best solution with “Speed” selection criterion in Case-IV that allows using boats unrestrictedly. Total delay (MoE_1) has the value of 42.69 hours at least whereas the optimization model provides 2.143 hours. The model also improves reaction time per incident (MoE_{12}) for four minutes. In this criterion, as boat capacities are unbounded, operation center assigns the fastest available boat for each incident that occurs in range. Thus, incidents near to the shore are responded in a short time, which decreases the total reaction time (MoE_{11}) and reaction time per incident (MoE_{12}) for sure. As stated in Table 4.8, bigger units have long range but low speed. Therefore, operation center assigns slower boats when the incident occurs far from the port (long distance), which undoubtedly causes delay.

To sum up, despite the improvement in reaction time per incident (MoE_{12}), a number of incidents are responded late even though the model allows using faster boats unrestrictedly. It is clear that the main reason of this problem is the data aggregation in optimization model. The optimization model utilizes each incident on the *superincident* of its zone whereas the SimModel-1 applies grid structure that generates the incident in nearly its real location and provides longer distances than

data aggregation. In some cases, the boat spends more time in proceeding to incident than the operation time on scene. Therefore, proceeding to far distances consumes considerable amount of supply from annual capacity and makes the boat out of order earlier than expected in terms of capacity limitation. In the beginning, the model responds to incidents within 30 minutes since all boat types are operable. However, reaction time to incident increases especially when faster boats start to get out of order. It can also be seen in Figure 4.15 and Figure 4.16 that response time to incidents rises up to 2-4 hours with capacity limitation.

To reveal the effects of data aggregation clearly, we generate SimModel-2 which utilizes 18 zones directly obtained from the optimization model. The results show that SimModel-2 dominates SimModel-1 in terms of total delay (MoE_1) and reaction time per incident (MoE_{12}). Even if there is a significant difference between optimization model and SimModel-2 in terms of total delay (MoE_1) in Case-I (optimization model assumption), SimModel-2 yields 97.45 and 128.278 hours of total delay that are approximately %50 lower than those of SimModel-1. The benefit of data aggregation in SimModel-2 rises to 60%-65% with higher percentages of relaxed capacity (Case-II and Case-III). However, SimModel-2 provides the best results when boats are utilized unrestrictedly with the "Speed" criterion (Case-IV). In this case, boats respond to all generated incidents with a total delay of 9.119 hours and reaction time per incident decreases to 17.3 minutes. According to this result, using grid structure to generate demand undoubtedly results in a five times worse result than the model with data aggregation. However, it can be assumed that 9.119 hours of total delay in 716 incidents is negligible and SimModel-2 gets close to the optimization model in terms of total delay (MoE_1).

Along with data aggregation, scheduling is another reason for the delays in the system. The optimization model locates SAR resources according to supply-demand relation and does not consider scheduling which is also an important factor that deteriorates performance of the optimization model. In real world, more than one incident may occur simultaneously and there could not be enough idle resources to respond them all. In that case, the incident waits for an idle boat and delay happens. As we develop two DES models, scheduling factor is taken into consideration and causes delays in a number of incidents.

The other factor that causes delay in the system is the stochastic demand data. We

believe that solving simulation models by using the “exact” locations of the incidents as in optimization model would be a repetition of the past in terms of model input data. Instead, we utilize stochastic demand that relies on historical data. We believe that this approach would enable models to represent the uncertainty. It also helps the model to be tested for different demand sizes. On the other hand, this demand variability affects operation matters and causes difference in solutions.

The analysis shows that optimization model with weighting and data aggregation (ZDM) provides an analytic method for decision makers to conduct SAR operations optimally. Applied weighting technique (Table 3.1) is a novel approach to determine the severity of incident types. Data aggregation helps avoid the cost of data collection and computing time. The short computing time leads to a flexible and applicable model to test other possible scenarios easily. In addition, generated zones with data aggregation display risky regions in the area of interest. Consequently, the optimization model incorporates multiple objectives into a single model bearing the decision makers’ preferences (weights) in mind and provides an optimal allocation scheme of boats while considering business rules and other restrictions.

Simulation models (SimModel-1 and SimModel-2) help to test the performance of the optimization model in realistic settings where scheduling and stochastic demand data are allowed. Comparison of both models reveals that data aggregation elicits an error in the model regarding the delay to incidents. In other respects, simulation models perform close to the optimization model with regard to total delay and reaction time per incident in the following cases:

- SimModel-1 with the “Speed” criterion in Case-IV (Figure 4.16),
- SimModel-2 with both criteria in Case-IV (Figure 4.17 and Figure 4.18).

In real life, we would expect that the operation center would assign the fastest boat without considering the remaining capacity at a given time. Thus, we believe that the analytic model is a good representation of the real world SAR operation process, and decision makers can apply it to manage their SAR organizations.

6 CONCLUSION

6.1 SUMMARY

In Chapter 1, general issues and objectives are stated. The main goal of this thesis is to create a methodology based on optimization and simulation to locate maritime SAR resources optimally while providing multiple objectives.

Chapter 2 contains a distinguished literature review of facility location, AHP, *k*-means clustering and DES. A number of studies whose important aspects we encompass are mentioned.

Chapter 3 introduces the details of our methodology in two sections: optimization and simulation model. In the first section, it clarifies how to determine incident severity and data aggregation beyond the model formulation. The second section presents the structure of the simulation model we utilized for evaluating the performance of the optimization model.

Chapter 4 introduces a case study in which we seek the allocation plan of maritime SAR resources among the ports in the Aegean Sea, the western region of Turkey. We try to locate 9 different types of SAR boats into 25 pre-defined ports referring to the historical incident data of the year 2014.

Chapter 5 states the results and discussions of the performed models.

In Chapter 6, conclusions, main findings and future work are presented.

6.2 CONTRIBUTIONS AND MAIN FINDINGS

We have developed a model (IB-BAM) for allocating SAR resources in an area of interest. The model consists of three steps: weighting incident types with AHP technique, data aggregation (ZDM) to generate demand data and mo-MIP optimization model that provides optimal allocation plan. It aims at minimizing the following three objectives: total weighted delay over critical time threshold, exceedance on budget and deviation on the annual operation capacity of boats. To observe its performance, we utilized our model to locate SAR resources into ports along the Aegean Sea. The model was performed for 15 different weighting

strategies. Results show that the optimization model helps decision makers respond to 716 incidents with only a three-minute delay in total. The sensitivity analysis shows that respond to incidents within a pre-defined time threshold is only achievable with the help of analytic approach which locates SAR resources optimally.

Along with this result, we developed simulation models (SimModel-1 and SimModel-2) to test results of the optimization model in real world settings. Scheduling and stochastic demand are considered and three different capacity policies are performed. Outputs of both models indicate that simulation models provide similar results with the optimization model under fully relaxed capacity policy.

6.3 FUTURE WORK

In this thesis, we applied deterministic inputs into the optimization model. As a future study, stochastic and fuzzy theory can be used to determine the demands in the problem. It enables forecasting future incident rates and also makes the model more flexible to deal with different possible scenarios.

As another future study, a combined model utilizing both aircrafts and surface units together may be developed to organize joint SAR operations.

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