OPTIMIZATION IN MATHEMATICAL MODELS OF POST-EARTHQUAKE SEARCH AND RESCUE

A THESIS SUBMITTED TO

THE GRADUATE SCHOOL OF ENGINEERING AND SCIENCE

OF BILKENT UNIVERSITY

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR

THE DEGREE OF MASTER OF SCIENCE

IN

INDUSTRIAL ENGINEERING

By

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June 2025

I certify that I have read this thesis and that in my opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Science.

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ABSTRACT

OPTIMIZATION IN MATHEMATICAL MODELS OF POST-EARTHQUAKE SEARCH AND RESCUE

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June 2025

Turkey is one of the world's most earthquake-prone countries, located on the highly active Alpine-Himalayan seismic belt. In the immediate aftermath of a major earthquake, the efficient allocation and scheduling of search and rescue (SAR) teams is critical for saving lives. This paper gives a brief summary of SAR activities in the aftermath of prior destructive earthquakes that happened in Turkey after 1990 and addresses the *quick search and rescue* problem, focusing on the first few hours following team deployment. We develop a deterministic optimization model for the assignment of professional SAR teams to disaster regions and the scheduling of their operations across collapsed sectors. The main aim of this study is to develop models that account for post-disaster uncertainty in demand and priority. To achieve this goal, we extend our model using minimax regret and α-reliable mean excess regret frameworks, enabling risk-aware decision-making under stochastic conditions. To improve the computational efficiency of the α-reliable mean excess regret model, we propose a heuristic algorithm that generates high-quality solutions by solving smaller scenario subsets iteratively. The best-performing heuristic solution is then used to warm-start the full stochastic model. Computational experiments are conducted using a simulated earthquake case based on real regional data from Hatay, Türkiye, with demand distributions generated using population-based scaling and randomization. Results show that our deterministic and stochastic models produce interpretable and realistic response strategies, while the heuristic yields near-optimal solutions. Moreover, the warm-start strategy significantly reduces the time required to reach optimality in large-scale instances.

Keywords: Search and rescue, decision-making under uncertainty, optimization, resource allocation, scenario analysis

ÖZET

DEPREM SONRASI ARAMA KURTARMA ÇALIŞMALARININ MATEMATİKSEL MODELLERİNDE OPTİMİZASYON

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Haziran 2025

Türkiye, aktif Alp-Himalaya deprem kuşağı üzerinde yer alması nedeniyle dünyanın en çok depreme maruz kalan ülkelerinden biridir. Büyük bir depremin hemen ardından, arama ve kurtarma (AK) ekiplerinin etkin şekilde bölgelere atanması ve çalışmalarının zamanlanması, insan hayatının kurtarılması açısından kritik öneme sahiptir. Bu çalışma, 1990 sonrası Türkiye'de meydana gelen yıkıcı depremlerin ardından yürütülen arama kurtarma faaliyetlerine dair kısa bir özet sunmakta ve ekiplerin görevlendirilmesini takip eden ilk saatlere odaklanan *hızlı arama kurtarma* problemini ele almaktadır. Bu kapsamda, profesyonel AK ekiplerinin afet bölgelerine atanması ve yıkılmış sektörler üzerindeki operasyonlarının zamanlanmasına yönelik deterministik bir optimizasyon modeli geliştirilmiştir. Çalışmanın temel amacı, afet sonrası talep ve öncelik düzeyindeki belirsizlikleri dikkate alan modeller geliştirmektir. Bu doğrultuda, geliştirilen model en kötü durum pişmanlığı (minimax regret) ve α-güvenilir ortalama fazla pişmanlık (mean excess regret) çerçeveleri ile genişletilmiş, böylece stokastik koşullar altında risk duyarlı karar verme olanaklı hale getirilmiştir. α-güvenilir ortalama fazla pişmanlık modelinin hesaplama verimliliğini artırmak amacıyla, daha küçük senaryo altkümeleri üzerinde yinelenerek çalışan ve yüksek kaliteli çözümler üreten sezgisel bir algoritma önerilmiştir. En iyi performans gösteren sezgisel çözüm, tam stokastik modelin çözümünü başlatmak (warm-start) için kullanılmıştır. Sayısal deneyler, Türkiye'nin Hatay iline ait gerçek bölgesel veriler kullanılarak oluşturulmuş simülasyon tabanlı bir deprem senaryosu üzerinden yürütülmüştür. Talep dağılımları, nüfus tabanlı ölçekleme ve rassallaştırma yöntemleriyle üretilmiştir. Sonuçlar, deterministik ve stokastik modellerin uygulanabilir ve gerçekçi müdahale stratejileri sunduğunu, önerilen sezgisel yaklaşımın ise yaklaşık optimal çözümler sağladığını göstermektedir. Ayrıca, önerilen warm-start stratejisinin büyük ölçekli problemlerde optimal çözüme ulaşmak için gereken süreyi önemli ölçüde azalttığı gözlemlenmiştir.

Anahtar sözcükler: Arama kurtarma, belirsizlik altında karar verme, optimizasyon, kaynak atama, senaryo analizi

Acknowledgements

I would like to express my deepest gratitude to my advisor, Prof. Bahar Yetiş Kara, for her invaluable guidance, unwavering support, and mentorship throughout the course of this thesis. Her insights and encouragement have been instrumental in shaping my work.

I am also sincerely thankful to Prof. Francisco Saldanha-da-Gama for his significant contributions to this research and to Dr. Zehranaz Dönmez Varol for her helpful input along the way. Their perspectives added meaningful value to my work.

I would like to thank the Industrial Engineering Department at Bilkent University—our faculty, my graduate friends, and Vegün Ekmekçi—for providing a supportive professional environment and foundation for my graduate studies. Special thanks go to Prof. Nesim Kohen Erkip and Assoc. Prof. Emre Nadar for their support and mentorship during my teaching assistantship, which enriched my academic experience beyond this thesis.

My graduate studies were supported by the TÜBİTAK BİDEB 2210 scholarship, and I gratefully acknowledge their financial support.

Finally, I extend my heartfelt thanks to my family and friends for their constant encouragement and support throughout this journey.

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Chapter 1

Introduction

Turkey is highly prone to natural disasters, the majority of which are earthquakes. According to statistics published by the Disaster and Emergency Management Authority (AFAD), earthquakes accounted for 92.6% of all natural events in Turkey in 2022 [2]. This high frequency is primarily due to Turkey's location along the Alpine-Himalayan seismic belt, one of the most active earthquake zones in the world. This seismic zone is responsible for approximately 20% of global earthquakes [3]. Given that a destructive earthquake occurs in Turkey approximately once every five years, scientific studies focusing on earthquakes play a critical role in reducing casualties and mitigating the impact of future earthquakes.

Building collapse is one of the most severe consequences of earthquakes. However, despite the life-threatening nature of structural failure, not all individuals trapped inside a collapsed building lose their lives [4]. A substantial proportion of those trapped can be rescued, provided that search and rescue (SAR) operations are conducted swiftly and effectively. Individuals trapped under rubble frequently face life-threatening conditions requiring urgent medical attention, such as inadequate access to clean air, severe blood and fluid loss, multiple injuries, compromised bodily integrity, and damage to internal organs and systems [5]. As a result, the probability of survival under collapsed structures decreases rapidly over time [6].

Kunkle [7] found that approximately 80% to 90% of survivors rescued from debris during disaster events were retrieved within the first 48 hours. Similarly, Comfort [8] reported that following the 1995 Kobe earthquake in Japan, 80.5% of survivors pulled from rubble on the first day were still alive. He underlined that this rate dropped to 28.5% on the second day, 21.8% on the third, and just 5.9% by the end of the fourth day. Quon and Laube [9] demonstrated that a 10% to 20% reduction in emergency response time could lead to a 1% to 2.5% decrease in mortality rates. In the 1988 Armenia earthquake, it was also found that 89% of survivors rescued from collapsed structures were located within the first 24 hours [10].

Due to the fact that the majority of individuals who survive under the rubble are rescued within the first 24 to 48 hours following an earthquake, rapid and well-coordinated SAR operations are critical in reducing fatalities [11]. However, both historical and recent earthquakes in Turkey have demonstrated significant challenges in achieving timely intervention. During the 1999 Marmara earthquake, a lack of immediate organizational response and resource shortages—such as heavy lifting equipment, SAR dogs, and trained personnel—resulted in delays, leaving initial rescue efforts largely in the hands of local residents [12]. Similarly, the 2023 Turkey-Syria earthquakes revealed vulnerabilities despite post-1999 preparedness reforms. The event was classified as a "Level 4" emergency, requiring national mobilization and international assistance. Yet, local response efforts were hindered by widespread regional impact, damaged transportation infrastructure, and insufficient SAR capacity in the early hours. Infrastructure failures and equipment shortages further limited the effectiveness of on-site teams, while night-time conditions and power outages made operational delays worse. Official records indicate a critically low number of SAR personnel deployed during the first 24 to 48 hours, precisely when survival chances are highest [1]. Details about the most recent major earthquakes in Turkey and SAR activities following them are presented in detail in Chapter 2.

As observed in previous destructive earthquakes, the SAR process is a complex and time-critical operation that requires the rapid organization and coordination of multiple teams. It is also a dynamic process with parameters that evolve over time. Efficient organization and the timely execution of rescue operations are essential to saving lives.

The identification of priorities and the allocation of resources accordingly are critical components of disaster management. For this reason, the disaster management process is typically divided into several time-dependent phases. Prior to an event, preparations are made for a potential disaster. Following the onset of a disaster, the process is divided into immediate response, followed by recovery, and finally reconstruction once the affected area is stabilized [13]. SAR operations are carried out in the immediate response phase, which occurs directly after the disaster event.

Information gathered from an interview with a volunteer that participated in SAR in Hatay during the 2023 Turkey-Syria earthquakes comfirm that SAR processes were coordinated by AFAD representatives at the Hatay Provincial Gendarmerie Command [14]. Serving as a centralized coordination hub, the center functioned as the primary interface for integrating teams affiliated with various organizations as well as individual volunteers. Aimed at ensuring rapid physical coordination, information flow, and cooperation, the coordination center significantly improved the effectiveness of SAR activities by addressing communication and organizational challenges across teams. According to INSARAG guidelines, such coordination centers—referred to as On-Site Operations Coordination Centres (OSOCC)—must be established immediately after an earthquake. The OSOCC is responsible for assigning SAR teams, scheduling their operations, and managing logistics

Following the immediate search and rescue efforts, post-earthquake humanitarian relief operations focus on addressing the essential needs of the affected population [4]. This phase includes the provision of emergency shelter, food, clean water, medical services, and psychosocial support. International aid organizations play a pivotal role during this period, coordinating with local authorities to ensure efficient delivery of assistance [15].

Temporary shelter is a critical component of early relief. Tents, prefabricated housing, and other forms of temporary accommodation are deployed to provide immediate protection and prevent secondary health risks. However, challenges such as inadequate waterproofing and insulation have been observed during previous disaster responses, leading to prolonged struggles for the affected population [16].

Donation campaigns and international fundraising efforts contribute significantly to the resources available for relief operations. These funds support logistics, supply chains, and long-term rebuilding initiatives. However, coordination of these resources remains a critical challenge for the decision makers. Bureaucratic delays and logistical bottlenecks have been reported in previous disaster settings, which highlights the need for effective resource management at all stages of disaster response around the world. [15].

In the reconstruction phase, the focus gradually shifts from emergency support to restoring infrastructure and housing. Modern recovery programs often follow the "Build Back Better" principle, which emphasizes not only rebuilding what was lost but also improving the structural system of the affected region and developing community resilience for future disasters. Thus, effective post-disaster recovery requires long-term planning and quick action, supported by coordination between local authorities, international organizations, and affected communities [17]. .

This study focuses on the immediate response phase of an earthquake, particularly the efficient assignment and scheduling of organized and well-equipped professional SAR teams via the OSOCC. While volunteers—both organized and spontaneous—play an important role in SAR efforts, they lack the required education and tools to conduct effective search and rescue. Professional teams, affiliated with specialized organizations such as AFAD, AKUT, and municipal fire departments, are capable of performing technically demanding tasks requiring advanced skills and specialized equipment. However, such teams are often delayed in reaching disaster zones compared to local or unorganized volunteers [5]. Given the limited availability of these qualified resources, rapidly matching equipped SAR teams with the regions that need them most is critical for operational effectiveness. Hence, this study aims to support such rapid deployment by optimizing the assignment and scheduling of well-equipped and professional SAR teams in the immediate aftermath of a disaster.

SAR is inherently a stochastic and time-sensitive process influenced by numerous uncertainties. In real-world post-disaster settings, especially in the chaotic hours following a major earthquake, factors such as the severity of destruction, population density, team and equipment availability, and secondary hazards (e.g., downed power lines, gas leaks, and flooding) cannot be fully known in advance. As such, perfect optimization of SAR efforts from the outset is unrealistic. Therefore, an initial phase known as quick search and rescue must be carried out using the teams already present in the disaster area. This phase targets maximum life-saving impact by acting during the critical first hours when survival rates are highest.

In this study, to balance the capturing the reality of the initial critical response period and computational efficiency, we focus on the first 13-hour window of the quick search and rescue phase, following the deployment of professional SAR teams. To support effective decision-making during this time-sensitive period, we first develop a deterministic optimization model that captures the assignment of teams to regions and the scheduling of operations within collapsed sectors. This model is then extended using minimax regret and α-reliable mean excess regret frameworks to account for uncertainty in sector-level demand and priority. The objective is to maximize the expected number of lives saved by enabling early and well-coordinated rescues under uncertainty through efficient assignment and scheduling of teams and equipment.

Recognizing that the applicability of detailed mathematical models may be constrained in chaotic, resource-limited real-world environments, this study aims to lead future studies that could generate implementable, data-driven strategies. By using mathematical models as decision-support tools, it is possible to derive practical and effective SAR policies under varying scenarios. The goal of developing mathematical models for SAR process is not only to optimize under ideal conditions but also to inform realistic strategies that can be applied in the field.

In addition to the core models, we introduce a heuristic solution method designed to efficiently approximate high-quality solutions for large-scale stochastic instances. By solving smaller subproblems repeatedly, the heuristic identifies strong candidate solutions that can be evaluated or improved further. We also implement a warm-start strategy, where the best heuristic solution is used to initialize the full stochastic model, leading to significant reductions in computation time. Extensive computational experiments across various regional and scenario configurations demonstrate the effectiveness of the proposed models and highlight the computational efficiency of the heuristic and warm-start practices that are introduced in the study.

The remainder of the study is organized as follows. Chapter 2 reviews the most recent destructive earthquakes that affected the Turkish population and how search and rescue processes were handled during those disasters. Chapter 3 summarizes the related literature, reviewing key papers from deterministic and stochastic disaster response as well as introducing the stochastic programming frameworks utilized in this study, namely minimax regret and α-reliable mean excess regret. Chapter 4 presents an extensive problem definition with our assumptions and introduces and explains the deterministic mathematical model. Chapter 5 introduces and explains the stochastic minimax and α-reliable mean excess regret models covered in this study. Chapter 6 presents the setting for our computational experiments and the numerical results of the experiments conducted with the deterministic model and the α-reliable mean excess regret model, as well as a sampling-based heuristic algorithm to reduce the computational time of the stochastic model and a warm-start strategy to further accelerate convergence to optimality. Chapter 7 concludes the work and presents opportunities and ideas for further study.

Chapter 2

Earthquakes and Search and Rescue in Turkey

2.1 Overview of Major Earthquakes in Turkey Since 1990

Turkey's geographical position renders it vulnerable to major earthquakes. Throughout its modern history, the country has experienced multiple high-impact earthquakes, but three in particular—the 1999 İzmit (Marmara), 2011 Van, and 2023 Kahramanmaraş (Turkey-Syria) earthquakes—stand out as the deadliest in terms of human loss since 1990. This section provides a structured overview of each event, highlighting their scale, geographic scope, and socio-economic consequences.

2.1.1 The 1999 İzmit (Marmara) Earthquake

On August 17, 1999, at 03:02 local time, a magnitude 7.4 earthquake struck the north-western region of Turkey, with its epicenter located near the town of Gölcük, approximately 90 km east of Istanbul. This event, commonly referred to as the İzmit or Marmara Earthquake, was one of the most devastating in the country's recorded history.

The earthquake ruptured approximately 150 kilometers of the North Anatolian Fault, with strong shaking lasting 37 seconds. The impact extended across seven provinces, most severely affecting the urban and industrial centers of Kocaeli, Sakarya, Yalova, and Istanbul. The official death toll reached 17,480, with over 23,000 people injured and approximately 250,000 rendered homeless. However, some independent estimates place the actual death count above 20,000 due to missing persons and undocumented fatalities.

Critical infrastructure was massively impacted. Nearly 300,000 housing units and over 40,000 commercial structures were either destroyed or heavily damaged. Key lifeline systems—including highways, railways, bridges, ports, and energy lines—were disrupted, and parts of Istanbul, Turkey's largest city, were left without electricity or water for days. The estimated economic cost of this disaster was over USD 6.5 billion, not including long-term business interruptions and recovery efforts.

The İzmit Earthquake exposed the fragility of Turkey's urban development, especially the prevalence of unregulated or poorly constructed buildings. It also revealed critical gaps in disaster preparedness and response capacity at both local and national levels. In the aftermath, it catalyzed major reforms in earthquake risk mitigation, urban planning, and institutional coordination for disaster management. [18]

2.1.2 The 2011 Van Earthquake

The second most deadly earthquake in Turkey after 1999 occurred on October 23, 2011, in the eastern province of Van. At 13:41 local time, a magnitude 7.2 earthquake struck the province with an epicenter located approximately 16 kilometers north of Van city, near the town of Tabanlı. The event occurred on a thrust fault in the Eastern Anatolian region, an area characterized by complex tectonics resulting from the collision of the Arabian and Eurasian plates.

The mainshock caused widespread destruction in Van and the nearby district of Erciş, where the majority of fatalities were recorded. Official figures reported 604 deaths, over 4,000 injuries, and approximately 11,000 collapsed or heavily damaged buildings. A second earthquake with a magnitude of 5.7 struck the region on November 9, just over two weeks later, resulting in additional casualties and the collapse of several buildings that had previously sustained damage, including the Bayram Hotel in Van city center.

While the death toll was considerably lower than the 1999 İzmit earthquake, the Van earthquake was particularly significant due to the challenging conditions in which emergency response efforts were conducted. Harsh winter weather, rugged terrain, and underdeveloped infrastructure hindered search and rescue operations and the delivery of emergency aid. Thousands were displaced in a region where temporary shelter options were limited and winter temperatures posed a serious threat to survival.

Damage was not limited to residential buildings. Public facilities including schools, hospitals, and government buildings also suffered structural failures. In Erciş, nearly 80% of the town's buildings were reported to be uninhabitable. The region's economic disruption, though less monetarily severe than the Marmara earthquake, was deeply felt due to its already fragile economic base and dependency on local commerce and agriculture.

The 2011 Van earthquake tested the institutional and logistical improvements made in Turkish disaster management after 1999. Although the national disaster agency AFAD (established in 2009) and military assets were mobilized quickly, the event still revealed delays in aid distribution, inconsistencies in information flow, and the absence of sufficient local SAR capacity. However, the presence of national coordination and broader public awareness of earthquake risk were cited as partial improvements compared to the 1999 disaster. [19]

2.1.3 The 2023 Turkey-Syria (Kahramanmaraş) Earthquakes

On February 6, 2023, Turkey experienced one of the deadliest and most destructive earthquakes in its modern history. At 04:17 local time, a magnitude 7.8 earthquake struck near the town of Pazarcık in Kahramanmaraş province, located in southeastern Turkey. Just nine hours later, at 13:24, a second powerful earthquake of magnitude 7.5 struck approximately 95 kilometers to the north, near the town of Elbistan, also in Kahramanmaraş. The dual earthquakes caused major devastation across 11 Turkish provinces and large parts of northwestern Syria, affecting an area home to more than 15 million people.

As of official reports, more than 50,000 people died in Turkey, with thousands more injured and tens of thousands displaced. In Syria, where data collection was more limited due to ongoing conflict, thousands more were reported dead. The earthquakes flattened residential neighborhoods, apartment blocks, hospitals, schools, and administrative buildings. In cities such as Antakya (Hatay), Adıyaman, Gaziantep, Malatya, and Şanlıurfa, entire districts were reduced to rubble (see Figure 2.1).

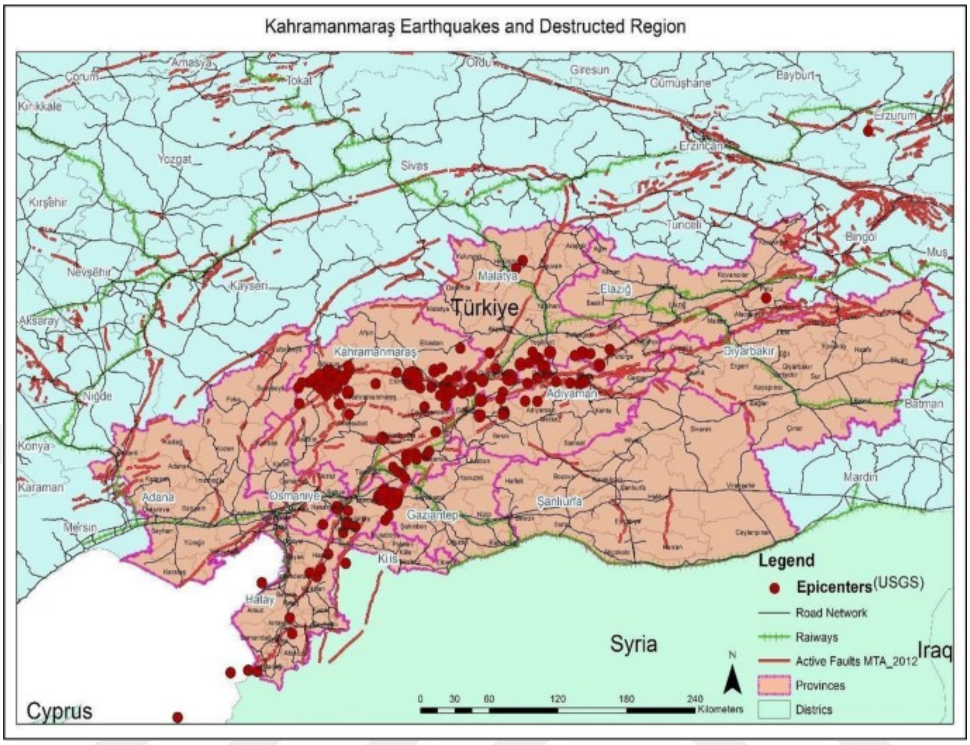

Figure 2.1: 2023 Turkey-Syria Eartquakes' Impact Area in Turkey [1]

The seismic impact of the February 6 events was among the most intense ever recorded in the region. The Pazarcık earthquake ruptured more than 300 kilometers of fault line across multiple segments of the East Anatolian Fault system. Ground accelerations were extremely high, and multiple aftershocks exceeding magnitude 6.0 followed in the days afterward. Thousands of buildings collapsed immediately, with many more becoming uninhabitable.

The destruction was compounded by several factors: the timing of the first quake during the early morning hours while most people were asleep, structural vulnerabilities in both urban and rural construction, and the scale of the affected area. In provinces like Hatay and Kahramanmaraş, where dense population centers coexisted with poorly regulated construction, the death toll was particularly severe.

Economically, the damage was catastrophic. The Turkish government estimated direct damage costs exceeding USD 100 billion, including residential and commercial infrastructure, roads, energy lines, and telecommunications. Major cultural heritage sites were also damaged, particularly in the historic city of Antakya. [1]

Together, the 1999 İzmit, 2011 Van, and 2023 Kahramanmaraş earthquakes constitute the three most lethal seismic events in Turkey since 1990. Each disaster revealed both the structural vulnerabilities of the built environment and the evolving capacity of national and local institutions to respond under extreme conditions. While improvements in disaster management infrastructure have occurred over the years, the scale and complexity of these events have highlighted challenges in rapid response, coordination, and logistical preparedness. The following section examines the search and rescue (SAR) efforts carried out during each of these earthquakes, focusing on team deployment, coordination mechanisms, logistical resources, and operational effectiveness.

2.2 SAR Operations During Major Earthquakes

2.2.1 SAR Operations During the 1999 İzmit Earthquake

The 1999 İzmit Earthquake caught Turkey's disaster response infrastructure unprepared for the scale and urgency of the emergency. In the initial hours following the earthquake, rescue operations were led primarily by civilians—survivors, neighbors, and family members—who attempted to dig through debris using bare hands and basic tools. Many of the initial rescues were improvised, uncoordinated, and often hindered by the lack of available equipment, trained personnel, and formal guidance.

In total, over 150,000 emergency responders were eventually mobilized throughout the disaster zone, including personnel from the Turkish Armed Forces, Civil Defense units, National Medical Rescue Teams (UMKE), fire brigades, and local municipalities. However, the official mobilization of these actors took several hours to days in some provinces. One of the most criticized aspects of the 1999 SAR effort was the lack of a centralized coordination mechanism, which resulted in logistical bottlenecks, duplication of effort in certain sites, and a complete absence of rescue activity in other areas.

International assistance played a critical role. SAR teams from over 25 countries—including the United States, Germany, Japan, Russia, Greece, and Israel—arrived within the first 48 hours, bringing with them trained personnel, search dogs, heavy equipment, and medical units. The contributions of these teams were especially effective in urban areas where structural collapse was most severe, such as Gölcük, Yalova, and parts of Istanbul.

One of the most significant logistical challenges was the absence of standardized equipment and communications infrastructure among domestic teams. Many units lacked listening devices, thermal cameras, cutting and lifting tools, and heavy machinery—resources that were readily available to their international counterparts. Transportation to and between affected cities was delayed due to collapsed roads and bridges, further complicating the allocation of rescue resources. [18]

2.2.2 SAR Operations During the 2011 Van Earthquake

The 2011 Van Earthquake served as the first major test of Turkey's post-1999 institutional reforms in disaster response, particularly the operational capacity of AFAD (Disaster and Emergency Management Authority), which was established in 2009 to unify Turkey's emergency management structure. While the disaster's geographic scope was more limited than the İzmit earthquake, its occurrence in a remote and underdeveloped region, combined with early winter conditions, posed serious logistical and operational challenges for SAR efforts.

Immediately following the mainshock on October 23, AFAD activated the National Disaster Response Plan and began coordinating the search and rescue teams from various regions of Turkey. A total of 6,865 SAR personnel were deployed to Van and Erciş within the first 48 hours, including AFAD teams, Turkish Armed Forces, UMKE, fire brigades, gendarmerie units, and volunteer organizations. International assistance also arrived quickly; over 30 countries offered help, with Iran, Azerbaijan, and Japan being among the first to deploy SAR personnel and technical support. (see Table 2.1).

Organization	Number of Personnel
AFAD (Disaster and Emergency Management Authority)	1,326
Turkish Armed Forces	2,064
UMKE (National Medical Rescue Teams)	513
Turkish Red Crescent	600
Fire Brigades (Various Provinces)	723
Gendarmerie Search and Rescue	410
Volunteer Organizations	629
International Teams	600
Total	**6,865**

Table 2.1: Search and Rescue Personnel Deployed During the 2011 Van Earthquake

The city of Erciş, which suffered the highest rate of fatalities and structural collapse, became the focal point of initial SAR activity. Urban areas were prioritized due to the high probability of mass entrapments. Rescue operations focused on collapsed multi-story apartment buildings, hotels, and public offices. AFAD deployed mobile coordination centers to both Erciş and Van city to facilitate communication between agencies, and for the first time, digital field coordination systems were used to track ongoing SAR operations.

Heavy search and rescue equipment—including hydraulic cutters, thermal imaging cameras, and listening devices—was airlifted into the region. Transportation delays and equipment shortages were still reported, particularly in smaller towns and rural areas. One of the major operational setbacks occurred during the second earthquake on November 9, which caused further building collapses—including previously damaged structures housing SAR personnel and journalists—and resulted in additional casualties, including the deaths of two international aid workers.

Emergency shelter and logistics were also part of the SAR mission. Temporary shelter infrastructure expanded rapidly after the initial SAR efforts, with over 100 tent cities established in Van province, accommodating more than 200,000 people in the first week (Table 2.2). UMKE and military medics provided mobile health services, trauma triage, and psychological support. Field hospitals were installed in open spaces near major population centers to handle overflow from the damaged hospitals.

Location	Tent Cities Established	Capacity (People)
Van City Center	38	75,000
Erciş	29	80,000
Surrounding Villages	35	45,000
Total	**102**	**200,000**

Table 2.2: Emergency Shelter Setup in Van Province (First Week Post-Earthquake)

While the 2011 Van Earthquake SAR response marked an improvement in institutional coordination compared to 1999, challenges remained. Many urban search and rescue teams were still under-equipped, inter-agency communication was inconsistent, and large numbers of volunteer responders were untrained and lacked proper tasking. Nevertheless, observers noted faster deployment, greater transparency, and a more centralized operational structure compared to previous disasters. [19]

2.2.3 SAR Operations During the 2023 Kahramanmaraş Earthquakes

The February 6, 2023 Kahramanmaraş earthquakes triggered the largest and most complex search and rescue (SAR) operation in the history of Türkiye. The vast geographic scale, high number of severely affected urban centers, and the existence of two massive earthquakes within a nine-hour span created a disaster environment that overwhelmed national capacity and required international involvement.

AFAD declared a Level 4 emergency immediately after the first earthquake, activating full national response protocols and initiating international assistance requests under the United Nations framework. Within hours, thousands of SAR personnel from AFAD, UMKE, the Turkish Armed Forces, fire departments, municipal SAR units, and voluntary organizations were deployed to the region. More than 35,000 domestic SAR workers were active in the field within the first 72 hours, in addition to nearly 11,000 foreign personnel from 90 countries. Major international contributors included teams from Azerbaijan, Israel, the United States, Russia, Greece, Japan, and numerous EU countries, many of which were INSARAG-certified heavy SAR units (Figure 2.2).

The earthquakes impacted 11 provinces in southern and southeastern Turkey, including Kahramanmaraş, Hatay, Gaziantep, Adıyaman, Malatya, and Şanlıurfa—requiring SAR teams to be distributed across a disaster zone larger than many European countries. Coordination was managed through OSOCCs established in several key cities. These centers facilitated information sharing, logistics, and the assignment of both domestic and international SAR teams. However, the large scale of the operation area created challenges in resource allocation, duplication of effort, and uneven coverage, especially in rural districts.

In Hatay and Kahramanmaraş, where urban areas were denser than the rest of the disaster area, structural collapse was near total and SAR efforts faced extreme conditions. Damage to transportation infrastructure delayed the arrival of heavy equipment and slowed the movement of personnel. Many initial rescues were carried out manually by civilians and early-arriving units, with minimal equipment. As roads were cleared and coordination improved, heavier machinery—cranes, thermal imaging, sound detection systems, and trained K9 units—became operational. Despite this, collapsed buildings remained uncleared for days in some neighborhoods due to overwhelmed capacity and prioritization triage.

AFAD reported that more than 160,000 rescue and relief workers participated across the two weeks following the earthquakes. SAR operations officially concluded by February 20, 2023, although isolated rescues continued up to the 12th day post-disaster. The survival window statistics echoed earlier disasters: the vast majority of live rescues occurred within the first 72 hours, underscoring the crucial importance of speed and logistical readiness in future large-scale responses.

Shelter and medical response efforts were implemented alongside SAR operations. The

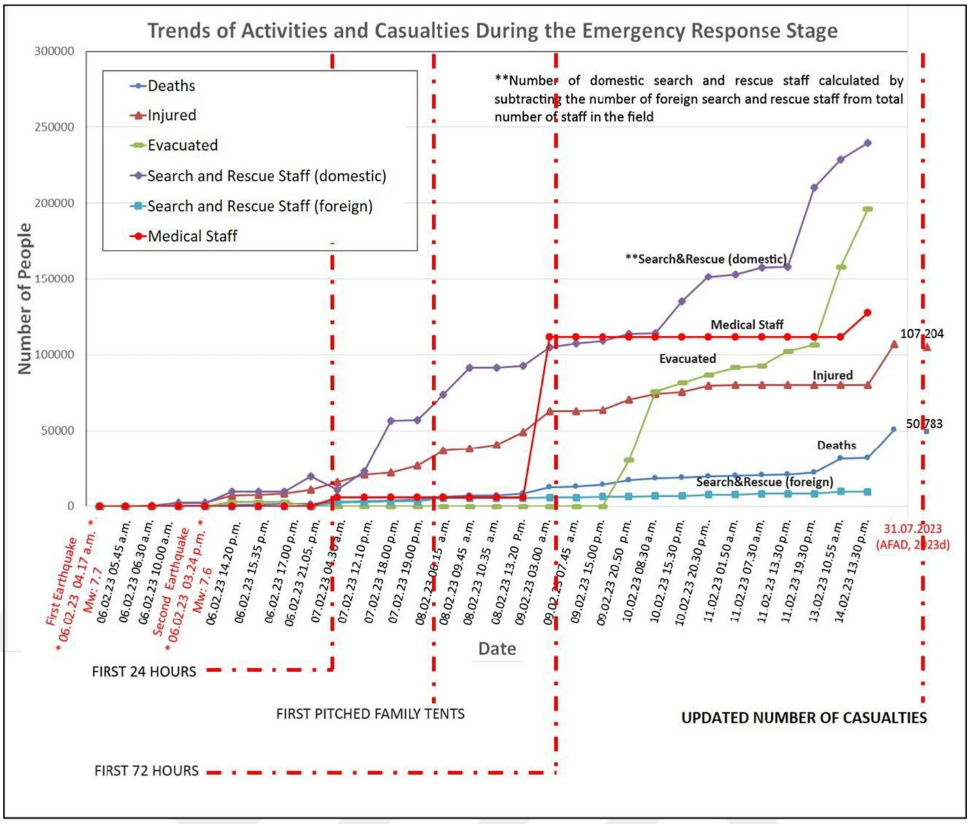

Figure 2.2: Trends of Activities and Casualties During the Emergency Response Stage in Turkey-Syria Earthquakes [1]

Turkish Red Crescent, AFAD, and Turkish Armed Forces established field hospitals, distributed over 300,000 tents, and deployed mobile kitchens, showers, and sanitation units. The logistical scale of this deployment was unseen in Turkish disaster history. However, public criticism targeted delays in response, especially in the early hours in provinces like Hatay, where communications infrastructure was destroyed and local coordination failed to mobilize quickly. The disaster also revealed bottlenecks in national inventory management, reliance on volunteer digital coordination networks (e.g., social media SAR tasking), and gaps in urban search-and-rescue coverage despite previous policy commitments.

The 2023 Kahramanmaraş earthquakes mark not only a humanitarian catastrophe, but also an important test for the Turkish SAR system. They demonstrated the utility of international coordination platforms like OSOCC, while also highlighting systemic challenges in logistics, communications, and task distribution. Lessons from this event are expected to shape future SAR protocols and capacity-building efforts across the region. [1]

2.3 Current Search and Rescue Capabilities in Turkey

2.3.1 Recent Developments in Turkey's SAR Capacity

In the wake of several major earthquakes over the past three decades, Turkey has made substantial investments to improve its national search and rescue (SAR) system. The Disaster and Emergency Management Authority (AFAD), as the centralized authority responsible for disaster coordination, has undertaken structural and operational reforms. According to AFAD's 2025 performance program, the agency currently oversees approximately 120,000 trained SAR personnel nationwide, with the number expected to reach 150,000 by 2027—positioning Turkey as one of the countries with the highest per-capita SAR capacity globally [20].

This expansion is supported by the accreditation of both governmental and non-governmental organizations. By 2025, AFAD projects that over 300 organizations will be certified to participate in coordinated SAR operations. Capacity-building efforts also include systematic regional trainings, public engagement campaigns, and the development of integrated technological systems for both planning and field operations.

AFAD's command and control system is written in the *Türkiye Afet Müdahele Planı* (TAMP, Turkish Disaster Response Plan), which defines the roles of 81 provincial directorates and 11 regional SAR bases. These units are further supported by a growing fleet of vehicles and technical equipment, including terrain-capable logistics trucks, mobile coordination centers, and reconnaissance UAVs. As of 2025, the national SAR fleet includes 1,051 operational vehicles, with a projected increase to 1,251 by 2027 [20]. Meanwhile, AFAD is rolling out real-time monitoring and alert systems such as the *Haber Alma Yayma Sistemi* (HAYS, Alert Dissemination System), remote sensing hazard maps, and GIS-supported decision platforms.

Turkey's development in SAR capacity also reflects an institutional commitment to inclusive and data-driven emergency response. AFAD's budgeting prioritizes integration of vulnerable populations—including children, the elderly, and disabled individuals—into planning and operational frameworks. Technological advancements like the *Yapı Sağlığı İzleme Sistemi* (YSİS, Structural Health Monitoring System) and a national disaster radio network are expected to support both early warning and on-site coordination by 2027.

2.3.2 Post-2023 Response and Capabilities

After being significantly tested by the dual earthquakes that struck the southeastern part of the country, efforts to improve the response capability for future disasters have gained acceleration. Following the 6.2 magnitude earthquake in Istanbul on April 23, 2023, authorities mobilized a comprehensive emergency response. According to official reports, over 11,000 personnel and 903 vehicles were deployed across affected districts. Emergency shelter was provided for more than 100,000 people through public facilities such as mosques and schools. Additionally, 308 food and water distribution points were established, supported by nearly 1,500 personnel and volunteers. Damage assessments were conducted on thousands of buildings, with minor damage reported in a small number of structures. No fatalities were reported, though 60 individuals received medical attention for injuries sustained primarily during evacuation efforts [21].

2.3.3 Search and Rescue Equipment and Vehicles

AFAD is reported to be expanding its fleet to enhance specialization of SAR operations in diverse field conditions. Equipment is categorized by mobility, function, and capacity. High-capacity deployment is supported by *İntikal Araçları* (Deployment Vehicles), which can carry 16 to 31 personnel and ensure access to remote or urbanized disaster zones [22]. For command and control, AFAD operates *Mobil Afet Koordinasyon Merkezleri* (Mobile Disaster Coordination Centers)—mobile offices equipped with data systems, communication infrastructure, and modular workspaces for up to 16 personnel.

In the field, SAR personnel utilize an array of tonnage-classified vehicles:

- **Hafif Tonajlı Araçlar** (Light-Tonnage Vehicles): Agile units for city operations, equipped with navigational and lifting systems.
- **Orta Tonajlı Araçlar** (Medium-Tonnage Vehicles): Vehicles equipped with 22 core tools including hydraulic cutters, audio-visual search systems, and field lighting.
- **Ağır Tonajlı Araçlar** (Heavy-Tonnage Vehicles): High-capacity intervention vehicles built on a 6x6 chassis, with 28-ton load capacity, integrated winches, and 360-degree rotating floodlights.

Other essential vehicles include *Kompakt Operasyon Araçları* (Compact Operation Vehicles), optimized for small-scale urban operations or lost-person scenarios, and *Haberleşme ve Görüntü Aktarım Araçları* (Communications and Image Transmission Vehicles), which enable satellite-based transmission from the field. In addition, AFAD has deployed *Mobil Deprem Simulasyon Araçları* (Mobile Earthquake Simulation Units) for use in public education and preparedness outreach.

AFAD also operates specialized SAR dog units known as *AFAD Arama Kurtarma Köpekleri* (AFAD Search and Rescue Dogs), which are trained over a two-year period in obedience, search behavior, scent detection, and field deployment. Dogs undergo rigorous certification in controlled environments and are matched with human handlers as part of operational SAR teams [23].

For chemical, biological, radiological, and nuclear (CBRN) emergencies, *AFAD KBRN Ekipleri* (CBRN Teams) deploy trained personnel equipped with protective gear and decontamination systems, aligned with international standards for hazard mitigation [24].

Information obtained from visiting the Ankara Fire Department shows that earthquake search and rescue equipment is organized into at least 14 distinct bags, each designed for a specific function and containing specialized tools. One example of a standard rescue bag is illustrated in Figure 2.3.

The empty bag itself weighs approximately 18 kg, and the total weight of the fully equipped bag reaches 69.9 kg. A listing of the contents of some of the search and rescue bags used by the Ankara Fire Department can be found in Appendix A.

In actual deployment, SAR teams from the Ankara Fire Department take with them a combination of different bags, chosen based on the anticipated structural conditions and operational needs. Although squads may divide into separate sub-teams, they retain the ability to share equipment internally, provided that units are operating within close proximity. This practice increases operational flexibility and reduces the need for duplication of specialized equipment.

Each equipment bag serves a unique function. Some are considered core to search and rescue operations, while others are situational—highly useful under specific conditions such as confined spaces, heavy concrete slabs, or unstable debris fields. This modular, shareable, and function-specific structure inspired the design of the optimization models introduced in the following chapters.

One of the core considerations in this study is the functional heterogeneity of search and rescue (SAR) equipment. The equipment brought to the disaster zone varies widely in purpose and utility—some tools are essential for cutting through reinforced concrete,

Figure 2.3: Contents list for SAR Bag No. 6, Ankara Fire Department

while others are suited for lighting, stabilization, or lifting. For example, hydraulic spreaders and rams (e.g., Boxes 4 and 6) are designed for breaching collapsed structures, while Box 3 contains pneumatic lifting bags used to elevate heavy rubble. Other kits, such as Box 8, are dedicated to lighting and power supply, and Box 7 contains chainsaws and concrete cutters for clearing dense debris. Recognizing that certain equipment types may be highly effective for specific rubble conditions but irrelevant or even unusable in others, the model incorporates equipment-sector compatibility to more realistically capture operational effectiveness during the quick response phase.

In addition to equipment heterogeneity, this study accounts for the organizational structure and logistical realities of SAR deployment. All squads assigned in a single instance are assumed to belong to the same professional SAR unit, such as a municipal fire department. While each squad brings a limited subset of equipment, once they are deployed and settled within a defined region, they operate in close proximity to each other. This enables the possibility of inter-squad equipment sharing. The proposed model incorporates this proximity-based sharing mechanism, allowing squads assigned to adjacent sectors within the same region to collectively access the available equipment pool.

Chapter 3

Related Literature

Resource allocation and scheduling during the emergency response phase of disasters has been an important focus in the operations research and management science (OR/MS) literature. Various streams of research have addressed this problem through deterministic and stochastic modeling approaches. This section reviews relevant studies, moving from general disaster response to those specifically focused on post-earthquake search and rescue (SAR), followed by an examination of stochastic modeling frameworks, namely minimax regret and α-reliable mean excess regret models.

Disaster response encompasses a wide range of activities carried out during and after the impact of a catastrophic event. Altay and Green [25] define disaster operations management as a sequence of steps involving mitigation, preparedness, response, and recovery. In this context, Operations Research and Management Science (OR/MS) techniques are applied to improve logistics, resource deployment, facility location, evacuation planning, and supply distribution related to a disaster. Their review organizes the literature by the stages of the disaster and identifies optimization, simulation, queuing, and decision theory as key methodologies used across various response settings. Galindo and Batta [26] extend this categorization and emphasize a growing trend in mathematical modeling, particularly highlighting the usefulness of OR/MS tools in pre- and post-impact decision-making environments.

A large body of OR/MS literature has focused on deterministic models to optimize resource allocation during disaster response. Rolland et al. [27] introduced the Disaster Response Scheduling Problem (DRSP), a deterministic variant of the multi-resource-constrained project scheduling problem, which was tested on synthetic earthquake scenarios. Their model incorporates operational constraints such as task precedence, resource availability, and deadlines, and uses the Adaptive Reasoning Technique (ART) for dynamic scheduling and reassignment. Rauchecker and Schryen [28] built on this framework, developing a branch-and-price algorithm to minimize weighted task completion times.

Wex et al. [29] proposed a nonlinear binary optimization model to assign and schedule heterogeneous SAR units to disaster incidents, including cases with co-allocation requirements. Their model was tested using synthetic instances resembling large-scale urban disasters, and they applied a Monte Carlo-based heuristic to outperform standard greedy baselines. Bodaghi and Palaneeswaran [30] developed a MILP model to assign non-expendable emergency teams such as fire brigades and medical units in a hypothetical Melbourne-based fire scenario, using realistic spatial data and uniform distributions to simulate incident severities and travel times.

In work more directly related to SAR, Wex et al. [31] introduced the Rescue Unit Assignment and Scheduling Problem (RUASP), developing a deterministic binary quadratic model solved through a combination of constructive heuristics and GRASP. Their computational evaluation involved artificial scenarios resembling urban earthquake responses. Schryen et al. [32] extended this with a collaborative version (RUASP/C), based on real-world coordination requirements, and implemented GREEDY and SCHED heuristics from scheduling literature. While these models effectively address resource-task matching and co-allocation, they do not explicitly account for the uncertainty present in real-world post-disaster environments.

One of the most critical aspects of disaster response is the presence of uncertainty, which arises from unpredictable demand levels, damaged infrastructure, fluctuating facility capacities, and limited or delayed information. Caunhye et al. [33] provide a comprehensive review of how such uncertainty is handled in emergency logistics, focusing on the use of probabilistic modeling, stochastic programming, robust optimization, and simulation techniques. They categorize the literature into key operational areas such as facility location, relief distribution, and casualty transportation, and conduct a detailed content analysis to highlight how different modeling strategies address uncertainty across these domains. Their findings emphasize that stochastic optimization has become a dominant tool for modeling disaster scenarios where coordination is complex, information is incomplete, and resources are constrained.

Stochastic programming has gained traction as a more realistic framework for disaster response due to the inherent uncertainties in demand, timing, and accessibility. Wang et al. [34] modeled emergency logistics under secondary hazard uncertainty using a two-stage stochastic program with probabilistic scenario generation. Zhang et al. [35] constructed a three-stage stochastic programming model for emergency logistics and resource distribution, using a combination of fuzzy programming and stochastic approximation to reflect uncertain transportation, costs, and unmet demand. Their work, tested on data from the 2008 Wenchuan earthquake, illustrates the complexity of cascading disaster effects.

Chen and Miller-Hooks [36] present one of the most directly relevant works to this study. They develop a multistage stochastic programming model for urban search and rescue team deployment in earthquake settings. Their model accounts for evolving situational awareness, uncertainty in demand and service times, and variable travel conditions. Solved via column generation and a sequence of two-stage problems, it is evaluated on a scenario based on the 2010 Haiti earthquake.

Ahmadi et al. [37] propose a two-stage robust MILP model for SAR resource allocation and routing under uncertainty, with a case study reflecting a hypothetical earthquake in Tehran. They use interval uncertainty to model demand and travel conditions and focus on both fairness and operational efficiency in district-level assignments. Wex et al. [38] also propose a fuzzy optimization model to account for vague or linguistically expressed variables such as task duration and severity. Their model, applied to synthetic earthquake response scenarios, uses a Monte Carlo heuristic for solution generation. Summary of the related literature can be found in Table 3.1

Despite these advances, few studies focus on the early-phase SAR operations under uncertainty—a critical window for saving lives—nor do they address the integration of scenario-based regret minimization in the allocation framework. This study proposes two-stage stochastic models whose structure significantly differ from those existing in the literature, particularly involving mostly binary decision variables for assignment and scheduling decisions.

This study also differs from other stochastic SAR optimization papers in the literature by introducing its heuristic algorithm, which decomposes the problem into deterministic problems after first-stage decisions are made.

The minimax regret criterion, originally introduced by Savage [39], focuses on minimizing the maximum possible regret across all scenarios. Regret is defined as the difference between the outcome of a chosen decision and the best possible outcome under a given scenario. Unlike expected value models, minimax regret does not rely on scenario probabilities, making it particularly suitable for decision-making in environments with severe uncertainty. In stochastic programming, the minimax regret model is commonly formulated as follows:

$$\min_{x \in X} \max_{\omega \in \Omega} \left[f(x,\omega) - f(x^*_\omega, \omega) \right],$$

where x denotes the decision variables, $\omega \in \Omega$ represents a scenario, $f(x,\omega)$ is the objective value under decision x in scenario ω, and x^*_ω is the optimal decision in scenario ω. This formulation explicitly focuses on controlling the worst-case deviation from scenario-specific optimality.

In the context of supply chain operations, minimax regret has been applied to strengthen the robustness of design and planning decisions. Liu et al. [40] developed a two-stage minimax relative regret model for resilient supply chain design under disruption and demand uncertainty. Their approach determines facility locations and investment decisions that minimize the maximum relative regret over all scenarios, thereby improving supply chain adaptability to rare but impactful events. Such applications demonstrate the suitability of minimax regret modeling for operational problems where worst-case performance carries critical importance.

While the minimax regret approach emphasizes protection against the worst-case scenario, it does not distinguish among the relative severity of bad outcomes across different scenarios. To address this, risk measures like Conditional Value-at-Risk (CVaR) have been introduced to provide a more nuanced, probability-weighted view of tail behavior. CVaR-based methods allow for greater modeling flexibility by incorporating the distribution of outcomes beyond a threshold, rather than focusing solely on the single worst-case. This perspective enables more balanced risk-aware decisions, especially in high-stakes, uncertain environments.

CVaR, also known as expected shortfall, represents the expected value of losses exceeding a specified quantile threshold of the loss distribution. Unlike Value-at-Risk (VaR), which only indicates the cutoff loss at a confidence level α, CVaR accounts for the average of the worst-case losses beyond that level. This distinction makes CVaR especially valuable in applications where understanding and controlling the magnitude of extreme losses is more important than merely identifying their boundary. Rockafellar and Uryasev [41] established that CVaR is a convex and continuous risk measure, allowing for efficient optimization even in discrete, scenario-based models where VaR may lead to unstable or non-convex formulations.

Conditional Value-at-Risk (CVaR). Let L be a loss random variable and let $\alpha \in (0,1)$ be the confidence level. The Conditional Value-at-Risk (CVaR) at level α, also known as the expected shortfall, is defined as the expected loss in the worst $(1-\alpha)$ tail of the distribution:

$$\mathrm{CVaR}_\alpha(L) = \min_{t \in \mathbb{R}} \left\{ t + \frac{1}{1-\alpha} \mathbb{E}[(L-t)^+] \right\},$$

where $(x)^+ = \max(x, 0)$ denotes the positive part. In a finite discrete scenario setting with W scenarios, where each scenario w has loss L_w and probability p_w, CVaR becomes:

$$\mathrm{CVaR}_\alpha(L) = \min_{t \in \mathbb{R}} \left\{ t + \frac{1}{1-\alpha} \sum_{w \in W} p_w \cdot \max(L_w - t, 0) \right\}.$$

Building on the theoretical foundations of CVaR, Chen et al. [42] introduced the α-reliable mean-excess regret (MER) model in the context of stochastic facility location problems. The α-MER model generalizes minimax regret by evaluating the expected regret over the worst-performing scenarios whose total probability mass does not exceed $1 - \alpha$. In doing so, the model combines the interpretability of regret-based frameworks with the tractability of CVaR-style formulations. The α-MER model remains convex and solvable via linear programming, making it suitable for a wide range of decision-making problems under uncertainty.

α-Reliable Mean Excess Regret. Let $R_w(x)$ denote the regret of decision x in scenario $w \in W$, and let π_w be the probability of scenario w. The α-reliable mean excess regret is defined as the minimum average regret over the worst-case subset of scenarios $S \subseteq W$ whose total probability mass does not exceed $1 - \alpha$:

$$\mathrm{MER}_\alpha(x) = \min_{S \subseteq W : \sum_{w \in S} \pi_w \leq 1-\alpha} \left\{ \frac{1}{\sum_{w \in S} \pi} \sum_{w \in S} p_w \cdot R_w(x) \right\}.$$

This formulation prioritizes reducing expected regret in the tail of the distribution, focusing robustness on high-impact, low-probability outcomes.

By penalizing not only the worst-case scenario but also the mean of a subset of bad outcomes, α-MER provides a more nuanced measure of regret, allowing decision-makers to hedge against extreme consequences without adopting overly conservative strategies. Empirical results in the original study demonstrate that the model achieves near-identical outcomes to the α-reliable minimax regret while offering substantial computational benefits [42].

In our study, the use of the α-MER model is particularly appropriate for post-earthquake search and rescue (SAR) operations, where decisions must be made under high uncertainty. The model offers a middle ground between average-case approaches, which can underestimate critical risks, and minimax models, which often result in overly conservative solutions [42]. By focusing on the worst-performing subset of scenarios, the α-MER framework enables robust and computationally tractable planning for high-impact, low-probability outcomes. Its compatibility with mixed-integer linear programming (MILP) formulations allows seamless integration into our SAR team assignment and scheduling problem.

This study introduces an assignment and scheduling framework for post-earthquake search and rescue (SAR) operations during the quick response period. A deterministic model is first developed and then extended using the minimax regret and α-reliable mean excess regret formulations to incorporate uncertainty in sector-level demand and priority scores.

To our knowledge, a CVaR-based approach has not been previously applied in SAR settings. Its scenario-based risk characterization makes it suitable for environments where information is incomplete or delayed. The study demonstrates the applicability of the α-MER model in a realistic SAR context and highlights its potential to support risk-aware decision making.

The deterministic model also introduces the assumption of intra-regional equipment sharing among squads assigned to the same region. This feature allows equipment brought by individual squads to be used by nearby teams, reflecting real-world coordination practices and improving overall resource utilization.

To address the computational complexity of the stochastic model, we propose a sampling-based heuristic that iteratively solves smaller scenario subsets to construct a high-quality first-stage solution. This solution is then input into the full-scale model, which becomes decomposable into deterministic subproblems. These are solved efficiently to generate a feasible solution for the original large-scale problem, which is then used as a warm start to accelerate convergence to optimality.

Paper	**Type**	**Objective**	**Model**	**Instance**	**Method**
Rolland et al. (2010) [27]	Det.	Task sequencing	DRSP (MRCPSP variant)	Synthetic (Hurricane-like)	Metaheuristic (ART)
Rauchecker & Schryen (2019) [?]	Det.	Weighted completion	DRSP, Branch-and-price	Synthetic	Exact (Branch-and-Price)
Bodaghi & Palaneeswaran (2016) [30]	Det.	Weighted completion	MILP	Hypothetical (Melbourne)	Exact
Wex et al. (2013) [31]	Det.c	Weighted completion	Non-linear binary	Simulated scenarios	Monte Carlo heuristic
Wex et al. (2014) [29]	Det.	Weighted completion	RUASP (Binary quadratic)	Simulated	Monte Carlo, GRASP
Schryen et al. (2015) [32]	Det.	Weighted completion	RUASP/C (MIQP)	Generated (Germany, THW-based)	Exact + Greedy, SCHED heuristics
Wex et al. (2016) [38]	Fuzzy	Weighted completion	Fuzzy optimization	Simulated (Japan 2011)	Monte Carlo
Chen & Miller-Hooks (2012) [36]	Stochastic	Max lives saved	Multistage stochastic	Haiti Earthquake (simulated)	Column generation
Ahmadi et al. (2020) [37]	Stochastic	Weighted completion	MILP (Two-stage)	Hypothetical (Tehran)	Exact
Wang et al. (2024) [34]	Stochastic	Resource distribution	2-stage stochastic	Generated scenarios	Exact
Zhang et al. (2019) [35]	Stochastic	Multi-objective	3-stage stochastic	Wenchuan Earthquake	Fuzzy MO, 2-stage SA
Our Study	Stochastic	Weighted completion	MILP (Two-stage)	Hatay, Türkiye (simulated)	Exact + Heuristic

Table 3.1: Classification of Relevant Literature on Disaster Response Resource Allocation and Scheduling

Chapter 4

Problem Definition and Formulation

Our deterministic problem formulation is based on information collected from individuals affiliated with organizations that conduct search and rescue operations in Turkey, specifically the Ankara Fire Department and the Turkish Disaster and Emergency Management Authority (AFAD). In Turkey, following an earthquake, a coordination center is established in an accessible part of the disaster area to facilitate the arrival and organization of search and rescue teams.

The initial hours after an earthquake are critical for setting up this coordination center and ensuring the deployment of local search and rescue squads. Ideally, OSOCC is constructed and made fully functional as soon as possible. Upon arrival at the OSOCC, search and rescue squads are assigned to specific regions where they conduct their operations. It is assumed that these squads bring their own specialized equipment to the disaster zone, with no access to additional resources until the later stages of the response effort.

In alignment with how real-world search and rescue (SAR) operations are organized by coordination centers in the aftermath of an earthquake, the affected area in this study is hierarchically divided into regions and sectors. Sectors represent operational SAR units—defined as either a single large structure or a cluster of collapsed buildings that are located close to each other. A sector may span a city block, a street segment, or a discrete high-priority structure, depending on the nature of the collapse and local urban topology. These sectors serve as the primary units where SAR squads perform search operations and spend substantial time conducting systematic interventions, including life detection, debris removal, and victim extraction.

Multiple sectors that are geographically adjacent or operationally interrelated are grouped into larger sections named regions. A region typically denotes the zone within which a squad will operate throughout the initial quick search and rescue period. Once a squad is deployed to a region, it is assumed to remain within that region for the duration of the operational timeframe considered in this model. Upon arrival, squads establish a temporary local coordination point—functioning as a base camp—where equipment is staged, daily operations are planned, and basic needs such as rest and sustenance are met. An illustrative example of the region and sector structure is presented in Figure 4.1, where the city of İskenderun is designated as one of the regions, and its corresponding region center and sectors are shown within its boundaries.

The objective of this problem is to maximize the amount of search and rescue work performed, with greater emphasis placed on work completed earlier in the response process. Additionally, the model prioritizes sectors with high importance while minimizing

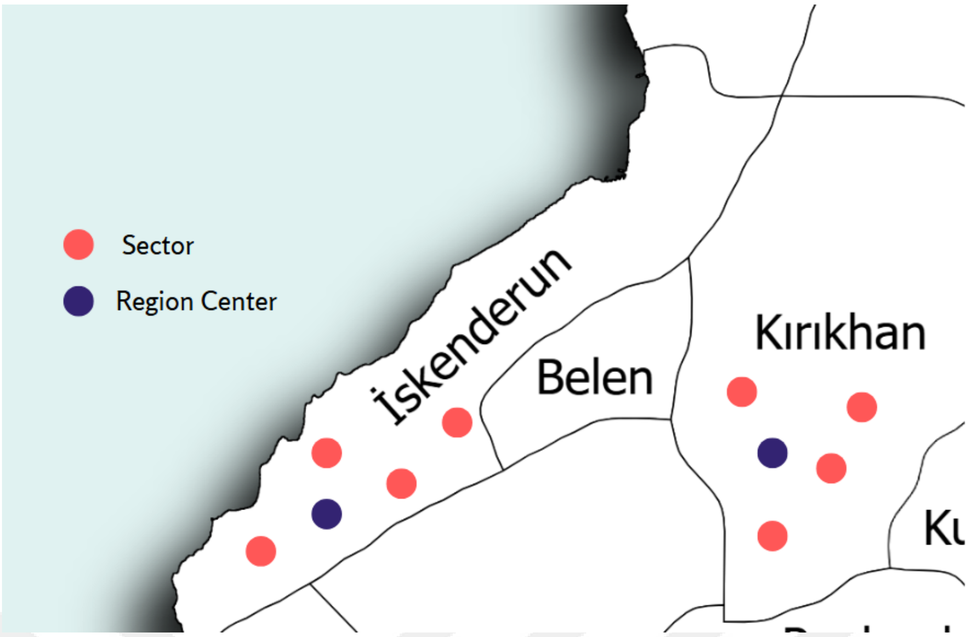

Figure 4.1: Illustration of region and sector structure on the Hatay map.

operations in high-risk areas. The objective function captures these key considerations, ensuring that resources are allocated efficiently to maximize early rescue efforts while strategically balancing priority and risk factors.

The rest of the assumptions underlying this problem setting are as follows:

- The squads assigned through the model work under the same organization. This assumption allows for intra-regional equipment sharing, as all squads operate within the same space. It is further assumed that equipment can be shared at any stage of the search and rescue process between discrete time units.
- In the deterministic modeling of the problem, the required workload for each sector, its priority level, risk factor, and the set of equipment that contributes most effectively to operations are assumed to be known. In contrast, the stochastic problem assumes that sector-specific workload, priority, and risk factors remain unknown until squad-region assignments are finalized.
- Once a squad begins operations in a sector, it has the flexibility to either continue working in that sector or leave at any time step. The quick search and rescue phase allows for partial completion of tasks, enabling squads to reallocate their effort to other sectors if doing so yields greater improvement in the overall objective. Any remaining work in the sector is assumed to be handled in subsequent stages of the search and rescue process.
- Each sector in the model is associated with two scores: risk and priority. In the stochastic version of the problem, these values are treated as uncertain and are revealed in the second stage, while in the deterministic version they are assumed to be known in advance. The risk score reflects safety concerns in the sector, such as fire, chemical leaks, or buildings at risk of secondary collapse, which may affect the feasibility of assigning squads. The priority score captures the importance of the sector from a rescue perspective and is based on factors such as population, reports

of trapped individuals, or the presence of critical infrastructure like hospitals or schools. Including both scores in the model allows for better representation of trade-offs between urgency and safety when planning search and rescue operations.

- Each sector has pre-determined boost factor respective to each equipment, previously assigned to it. The equipment boost factor parameter in this problem is motivated by the fact that different types of rubble require different types of equipment. We account for the possibility that certain equipment may be beneficial—or even essential—for accessing specific types of rubble, while in other cases, it may be redundant.

4.1 Deterministic Model

Sets

- I : Set of squads.
- N : Set of regions.
- J : Set of sectors.
- J_n : Set of sectors belonging to region $n \in N$.
- T : Set of discrete time units.
- K : Set of equipment.

Parameters

- TM : Parameter used to assign values to working times.
- H_{ik} :

$$H_{ik} = \begin{cases} 1, & \text{if squad } i \text{ is equipped with equipment } k \\ 0, & \text{otherwise} \end{cases}$$

- D_j: Demand of sector $j \in J$.
- α_j: Priority score of sector $j \in J$, in $\{1.25,\ 1.5,\ 1.75,\ 2\}$.
- β_j: Risk score of sector $j \in J$, in $\{0.25,\ 0.5,\ 0.75,\ 1\}$.
- B_{kj} : Boost factor for equipment $k \in K$ for sector $j \in J$.

Decision Variables

- s_{jt} :

$$s_{jt} = \begin{cases} 1, & \text{if work in sector } j \text{ begins at time } t \\ 0, & \text{otherwise} \end{cases}$$

- f_{jt} :

$$f_{jt} = \begin{cases} 1, & \text{if work in sector } j \text{ finishes at time } t \\ 0, & \text{otherwise} \end{cases}$$

- w_{jt} :

$$w_{jt} = \begin{cases} 1, & \text{if sector } j \text{ is being worked on at time } t \\ 0, & \text{otherwise} \end{cases}$$

- x_{jtk} :

$$x_{jtk} = \begin{cases} 1, & \text{if equipment } k \text{ is being used on sector } j \text{ at time } t \\ 0, & \text{otherwise} \end{cases}$$

- y_{in} :

$$y_{in} = \begin{cases} 1, & \text{if squad } i \text{ is assigned to region } n \\ 0, & \text{otherwise} \end{cases}$$

- P_{jt} : Amount of work done in sector j at time t.

Objective Function

$$\max \sum_{j \in J} \left[\sum_{t \in T} (TM - t) \cdot P_{jt} \right] \cdot (\alpha_j - \beta_j) \tag{4.1}$$

Constraints

$$\sum_{n \in N} y_{in} = 1, \quad \forall i \in I \tag{4.2}$$

$$\sum_{j \in J_n} w_{jt} \leq \sum_{i \in I} y_{in}, \quad \forall t \in T, \forall n \in N \tag{4.3}$$

$$\sum_{t \in T} s_{jt} \leq 1, \quad \forall j \in J \tag{4.4}$$

$$\sum_{t \in T} f_{jt} \leq 1, \quad \forall j \in J \tag{4.5}$$

$$\sum_{t' < t} s_{jt'} \geq f_{jt}, \quad \forall t \in T, \forall j \in J \tag{4.6}$$

$$\sum_{t' \leq t} s_{jt'} \geq w_{jt}, \quad \forall t \in T, \forall j \in J \tag{4.7}$$

$$w_{jt} + s_{j,t+1} - f_{jt} = w_{j,t+1}, \quad \forall j \in J, \forall t \in T \tag{4.8}$$

$$w_{jt} \geq x_{jtk}, \quad \forall j \in J, \forall t \in T, \forall k \in K \tag{4.9}$$

$$\sum_{j \in J_n} x_{jtk} \leq \sum_{i \in I} y_{in} H_{ik}, \quad \forall t \in T, \forall k \in K, \forall n \in N \tag{4.10}$$

$$\sum_{k \in K} x_{jtk} B_{kj} \geq P_{jt}, \quad \forall j \in J, \forall t \in T \tag{4.11}$$

$$D_j \geq \sum_{t \in T} P_{jt}, \quad \forall j \in J \tag{4.12}$$

$$s_{jt}, f_{jt}, w_{jt}, x_{jtk}, y_{in} \in \{0,1\}, \qquad \forall j \in J, \forall t \in T, \forall k \in K, \forall i \in I, \forall n \in N \tag{4.13}$$

$$P_{jt} \geq 0, \qquad \forall j \in J, \forall t \in T \tag{4.14}$$

The objective function (4.1) seeks to maximize the total time-weighted and risk-adjusted work value achieved across all sectors. Specifically, for each sector j, the amount of work performed at time t, denoted by P_{jt}, is weighted by the remaining time horizon $(TM - t)$, reflecting a preference for earlier completions in the quick search and rescue phase.

TM is a fixed parameter greater than $|T|$, used to assign time-based weights to completed work. Specifically, $TM - t$ represents the value of work completed at time unit t, allowing earlier completion to be prioritized. Adjusting TM controls the sensitivity of this weighting: a larger TM results in smaller differences between time units, reducing the emphasis on early completion. For instance, with $TM = 20$, the relative values for time units 7 and 8 are 13 and 12 $\left(\frac{13}{12} \approx 1.08\right)$, whereas with $TM = 13$, the values are 6 and 5 $\left(\frac{6}{5} = 1.2\right)$, placing greater emphasis on earlier work.

Time-weighted work is then scaled by the net priority of the sector, given by the difference between its priority score α_j and risk score β_j. Higher priority sectors and sectors with lower operational risk contribute more positively to the objective.

The constraints in the model collectively ensure the feasibility of squad assignments, the logical sequencing of search and rescue operations across time and space, and the consistent use of equipment within operational limits.

Constraint (4.2) ensures that each squad is assigned to exactly one region. This reflects the assumption that once a squad is deployed to a region during the quick search and rescue phase, it remains there for the entire duration of the operation. Constraint (4.3) imposes a limit on the number of active sectors in each region at any given time, ensuring that the number of simultaneously active sectors does not exceed the number of squads assigned to that region. This captures the operational limitation that each sector requires at least one squad to be actively working in it.

Constraints (4.4) and (4.5) enforce that a sector can have at most one start time and one finish time, respectively. These constraints ensure the activity window of each sector is clearly defined and non-redundant. Constraint (4.6) links these timing decisions by ensuring that no sector can be declared finished before it has started. This sequencing logic enforces time consistency in the activation and completion of search and rescue tasks. Similarly, Constraint (4.7) ensures that work in a sector cannot proceed until the sector has been declared started, preventing equipment usage and labor effort from being allocated prematurely.

Continuity of work is modeled through Constraint (4.8), which ensures that once work in a sector begins, it either continues in the next time period or is formally completed. This maintains temporal consistency in sector activity and eliminates gaps or isolated activation periods. Constraint (4.9) ensures that equipment is only used in sectors where work is being actively performed, avoiding resource allocation to inactive locations.

Resource feasibility is further addressed in Constraint (4.10), which ensures that the total equipment used across all sectors in a region and time period does not exceed the total equipment brought to the region by assigned squads. This reflects logistical constraints in disaster response where equipment availability is tightly linked to deployment decisions. Constraint (4.11) connects equipment usage with work output by requiring that the total boost-adjusted equipment effort allocated to a sector at a given time meets or exceeds the declared work potential. Finally, Constraint (4.12) ensures that the total amount of work performed in a sector does not exceed its overall demand, maintaining feasibility with respect to sectoral needs.

Chapter 5

Stochastic Models

This chapter extends the deterministic model by incorporating uncertainty through a scenario-based stochastic programming framework. In real-world post-disaster operations, key inputs such as demand levels, priority scores, and safety risks are often not known with certainty at the time decisions are made. To address this, we formulate two-stage stochastic models in which squad-to-region assignments are made before the realization of uncertain parameters, and operational scheduling is optimized after scenarios are revealed.

We explore two modeling approaches for handling regret under uncertainty: the *minimax regret model*, which minimizes the worst-case scenario regret, and the *α-reliable mean excess regret model*, which focuses on minimizing the average regret over a subset of worst-performing scenarios. Both approaches evaluate solution quality relative to scenario-specific optimal outcomes and offer distinct trade-offs between conservativeness and computational traceability.

5.1 Minimax Regret Model

The minimax regret approach focuses on identifying a solution that performs best in the worst-case scenario, measured by the deviation from the optimal outcome in each realization. The core idea is to minimize the maximum regret, defined as the loss in objective value compared to a scenario-optimal solution. This leads to a solution that is robust against the most unfavorable realization.

In the context of search and rescue planning, the minimax regret model serves as a conservative planning tool by guaranteeing that the performance loss is bounded across all potential disaster scenarios. It is particularly appropriate in situations where decision-makers aim to avoid high-regret outcomes under any realization, even at the expense of average-case performance. The resulting model requires computing optimal values for each scenario and then enforcing that the regret in all scenarios does not exceed a minimized threshold.

5.1.1 Mathematical Formulation of Min-max Regret Model

This model utilizes sets and parameters from the deterministic model from Section 4.1 with a few additions. Only newly added sets and parameters are explained below.

Sets

- Ω : Set of deterministic scenarios, indexed by ω.

Parameters

- μ_ω^* : Optimal objective value of deterministic scenario $\omega \in \Omega$.

Decision Variables

- η : Maximum regret.
- s_{jtw} :

$$s_{jtw} = \begin{cases} 1, & \text{if work in sector } j \in J \text{ begins at time } t \in T \text{ when scenario } \omega \in \Omega \text{ is realized} \\ 0, & \text{otherwise} \end{cases}$$

- f_{jtw} :

$$f_{jtw} = \begin{cases} 1, & \text{if work in sector } j \in J \text{ finishes at time } t \in T \text{ when scenario } \omega \in \Omega \text{ is realized} \\ 0, & \text{otherwise} \end{cases}$$

- w_{jtw} :

$$w_{jtw} = \begin{cases} 1, & \text{if sector } j \in J \text{ is being worked on at time } t \in T \text{ when scenario } \omega \in \Omega \text{ is realized} \\ 0, & \text{otherwise} \end{cases}$$

- x_{jtkw} :

$$x_{jtkw} = \begin{cases} 1, & \text{if equipment } k \in K \text{ is being used on sector } j \in J \\ & \text{at time } t \in T \text{ when scenario } \omega \in \Omega \text{ is realized} \\ 0, & \text{otherwise} \end{cases}$$

- P_{jtw} : Amount of work done in sector $j \in J$ at time $t \in T$ when scenario $\omega \in \Omega$ is realized.

Objective Function (Minimax Regret)

$$\min \eta \tag{5.1}$$

Constraints

$$\eta \geq -\sum_{j \in J} \left[\sum_{t \in T} (TM - t) P_{jtw} \right] (\alpha_{j\omega} - \beta_{j\omega}) + \mu_\omega^*, \quad \forall \omega \in \Omega \tag{5.2}$$

$$\sum_{n \in N} y_{in} = 1, \quad \forall i \in I \tag{5.3}$$

$$\sum_{j \in J_n} w_{jtw} \leq \sum_{i \in I} y_{in}, \quad \forall t \in T, \forall n \in N, \forall \omega \in \Omega \tag{5.4}$$

$$\sum_{t \in T} s_{jtw} \leq 1, \quad \forall j \in J, \forall \omega \in \Omega \tag{5.5}$$

$$\sum_{t \in T} f_{jtw} \leq 1, \quad \forall j \in J, \forall \omega \in \Omega \tag{5.6}$$

$$\sum_{t' < t} s_{jtw} \geq f_{jtw}, \quad \forall t \in T, \forall j \in J, \forall \omega \in \Omega \tag{5.7}$$

$$\sum_{t' \leq t} s_{jtw} \geq w_{jtw}, \quad \forall t \in T, \forall j \in J, \forall \omega \in \Omega \tag{5.8}$$

$$w_{jtw} + s_{j,t+1,\omega} - f_{jtw} = w_{j,t+1,\omega}, \quad \forall j \in J, \forall t \in T, \forall \omega \in \Omega \tag{5.9}$$

$$w_{jtw} \geq x_{jtkw}, \quad \forall j \in J, \forall t \in T, \forall k \in K, \forall \omega \in \Omega \tag{5.10}$$

$$\sum_{j \in J_n} x_{jtkw} \leq \sum_{i \in I} y_{in} H_{ik}, \quad \forall t \in T, \forall k \in K, \forall n \in N, \forall \omega \in \Omega \tag{5.11}$$

$$\sum_{k \in K} x_{jtkw} B_{kj} \geq P_{jtw}, \quad \forall j \in J, \forall t \in T, \forall \omega \in \Omega \tag{5.12}$$

$$D_{j\omega} \geq \sum_{t \in T} P_{jtw}, \quad \forall j \in J, \forall \omega \in \Omega \tag{5.13}$$

$$s_{jtw}, f_{jtw}, w_{jtw}, x_{jtkw} \in \{0, 1\}, \qquad \forall j \in J, \forall t \in T, \forall k \in K, \forall \omega \in \Omega \tag{5.14}$$

$$\eta \geq 0 \tag{5.15}$$

$$P_{jtw} \geq 0, \qquad \forall j \in J, \forall t \in T, \forall \omega \in \Omega \tag{5.16}$$

The objective function (5.1) minimizes the maximum regret across all scenarios. Here, η represents the upper bound on the regret that the solution may incur in any scenario $\omega \in \Omega$. Constraint (5.2) defines the regret expression for each scenario. The inner term calculates the objective value of the current solution in scenario ω, using the total time-weighted work $\sum_{t \in T}(TM - t)P_{jtw}$ scaled by the net priority $(\alpha_{j\omega} - \beta_{j\omega})$. This value is subtracted from the scenario-specific optimal value μ^*_ω to obtain the regret. The constraint ensures that this regret does not exceed the decision variable η, which is shared across all scenarios. As a result, η serves as a uniform upper bound on regret.

Constraint (5.3) guarantees that each squad is assigned to exactly one region, a global assignment decision that remains fixed across all scenarios. Constraint (5.4) restricts the number of simultaneously active sectors in a region to not exceed the number of squads assigned to that region, for every scenario and time period. Constraints (5.5) and (5.6) ensure that each sector starts and finishes work at most once per scenario, while Constraint (5.7) enforces a consistent ordering by preventing any sector from finishing before it has started.

Constraints (5.8) and (5.9) handle the logical flow of work over time. The former ensures that a sector cannot be active before being started, and the latter enforces temporal continuity—once work begins, it must either continue or conclude. Constraint (5.10) ensures that equipment is only used in sectors where work is actively being conducted.

Constraint (5.11) ensures that, in each scenario, the total equipment usage across sectors within a region does not exceed the total equipment transported to the region by the squads assigned there, based on the squad-equipment availability parameter H_{ik}.

Constraint (5.12) links equipment usage to sector-level productivity. It ensures that the declared work potential P_{jtw} at a given sector and time is supported by the cumulative effect of the equipment used, scaled by sector-specific boost factors B_{kj}. Finally, Constraint (5.13) limits the total work performed in each sector to not exceed its scenario-specific demand $D_{j\omega}$. This enforces feasibility with respect to uncertain but bounded demand, and ensures that the model avoids over-allocating effort to any single sector in any realization.

5.2 α-Reliable Mean Excess Regret Model

While the minimax regret model provides strong guarantees against the worst-case scenario, it treats all adverse outcomes equally and does not account for how frequently or severely poor outcomes might occur. To address this limitation, the α-reliable mean excess regret (MER) model focuses on minimizing the expected regret over the worst-performing scenarios that jointly represent a probability mass of at most $1-\alpha$.

This model combines regret-based reasoning with the structure of Conditional Value-at-Risk (CVaR) which allows for a more balanced treatment of risk. Instead of minimizing regret in a single worst-case scenario, the α-MER model penalizes regret across a set of high-impact scenarios. In the search and rescue context, this approach enables robust and efficient planning by focusing protection on a portion of the worst-case distribution while maintaining traceability of the computational model.

In the context of post-earthquake search and rescue squad assignment and scheduling, we incorporate the α-MER criterion to mitigate the impact of uncertain demand distributions. The model seeks to minimize the mean excess regret beyond a specified reliability threshold α, ensuring that the solution remains effective for all potential realizations.

Implementation within our stochastic SAR optimization framework involves generating earthquake demand scenarios using arbitrary probability distributions. The regret function is computed as the deviation between the objective value of the selected assignment decision and the optimal objective value for the deterministic case of each scenario. The objective function incorporates α-MER to control excessive regret. This formulation enables a more structured response to demand uncertainty and balances computational efficiency and robustness in SAR resource allocation.

5.2.1 Mathematical Formulation of α-MER model

Sets, parameters and decision variables of this problem are exactly the same as given in Section 5.1 with a few differences denoted below.

Parameters

- γ : Reliability parameter.
- π_ω : Probability of scenario $\omega \in \Omega$ occurring.

Decision Variables

- η : Regret threshold.
- ψ_ω : Excess regret of scenario $\omega \in \Omega$.

Objective Function

$$\min \eta + \frac{1}{1-\gamma} \sum_{\omega \in \Omega} \pi_\omega \psi_\omega \tag{5.17}$$

Constraints

$$\psi_\omega \geq -\sum_{j \in J} \left[\sum_{t \in T} (TM - t) P_{jtw} \right] (\alpha_{j\omega} - \beta_{j\omega}) + \mu^*_\omega - \eta, \quad \forall \omega \in \Omega \tag{5.18}$$

$$\text{Constraints 5.3–5.16} \tag{5.19}$$

The objective function (5.17) minimizes the γ-reliable mean excess regret across all scenarios. The variable η represents a scenario-independent regret threshold, while ψ_ω measures the amount by which the regret in scenario ω exceeds this threshold. Each scenario $\omega \in \Omega$ is associated with a probability π_ω. The second term in the objective scales the total excess regret over all scenarios by $\frac{1}{1-\gamma}$, thereby capturing the average regret in the worst-performing $(1-\gamma)$ tail of scenarios. This structure mirrors the Conditional Value-at-Risk (CVaR) approach, enabling a risk-sensitive objective that emphasizes robustness in rare but high-impact outcomes.

Constraint (5.18) defines the scenario-wise excess regret ψ_ω as the gap between the realized objective value in scenario ω and the optimal objective value μ^*_ω for that scenario, adjusted by the threshold η. This constraint ensures that only scenarios where the regret exceeds η contribute to the excess regret term in the objective. It serves as the key mechanism for isolating the tail performance and guiding the optimization to avoid poor outcomes in critical scenarios.

Chapter 6

Computational Experiments

This chapter presents the computational experiments conducted to evaluate the performance of the deterministic model and its stochastic extension, followed by the introduction of the heuristic algorithm and a warm-start strategy that uses the results of the algorithm to improve solution efficiency.

6.1 Example Dataset

The equipment data for this problem is constructed by analyzing and generalizing the real search and rescue equipment sets based on information provided by the Ankara Fire Department. As presented in Chapter 2, search and rescue organizations store their equipment in carrying units referred to as "rescue bags." Each rescue bag is assigned a unique identification number and contains a predefined set of equipment, along with the quantity and weight of each item, which is documented on the lid of the box. These rescue bags are transported to disaster areas by rescue squads. While the contents and sizes of rescue bags vary, the number of unique rescue bag types is limited. Therefore, in this study, we assume that the equipment set K consists of 12 unique rescue bag types, each representing a standardized set of equipment. Multiple rescue bags of the same type may be deployed across different disaster areas, regions, and teams.

To balance accuracy and computational efficiency, we define three discrete values for the boost factor. Specifically, $B_{kj} = 1$ indicates that the equipment is somewhat useful for sector j, $B_{kj} = 2$ signifies that it is useful, and $B_{kj} = 5$ denotes that the equipment is highly useful or potentially necessary. The boost factor values are randomized for this problem but remain consistent across different experimental settings to ensure the comparability of results.

In the example dataset of this problem, region, sector, and demand data are synthetically constructed but inspired by real administrative divisions and population figures from the Hatay province in Türkiye. The setup includes six regions representing provinces and 45 sectors corresponding to neighborhoods, forming a case-study-like setting suitable for testing the deterministic and stochastic models, as well as the heuristic algorithm. Sector-level demand values are based on actual population data from each neighborhood, scaled appropriately to reflect the working capacity of squads and equipment within the model's time units.

To maintain realistic yet computationally manageable job durations, sector demands were scaled down proportionally with respect to population. For instance, the sector *Esentepe* in the Reyhanlı region is modeled as a medium-effort zone within the first 12-

hour of the quick search and rescue window. It is assigned a demand value of 73, which corresponds to approximately 9 hours of work if a squad enters the sector equipped with three tools having boost factors of 1, 2, and 5, respectively. The rest of the demand values follow a similar logic, maintaining proportionality with population while reflecting sector-specific workload assumptions.

Higher-population neighborhoods such as *Çekmece* and *Harbiye* in the Defne region are modeled with higher demand values. These sectors are intentionally designed to exceed the 12-hour operational capacity of a typical squad, capturing the reality that highly populated areas require extended operations beyond the initial phase. The complete list of regions, sectors, and demand values is provided in Table 6.1.

This table presents the demand structure for scenarios in which 2, 4, and 6 regions are considered. The primary focus of this study is on the regions of Antakya and Defne, which constitute the core 2-region scenario. In the 4-region case, the rural areas of Reyhanlı and Samandağ are incorporated to assess the impact of rural settings on the problem. The 6-region scenario further introduces İskenderun, an urbanized area, and Erzin, another rural area.

The priority (α_j) score assigned to each sector are determined based on demand levels, incorporating a probabilistic weighting scheme to reflect sector-specific urgency. Sectors are first categorized into three demand levels: low (demand $\leq$ 200), medium (200 $<$ demand $\leq$ 400), and high (demand $>$ 400). The priority score α_j is then assigned using a weighted random selection, where low-demand sectors are more likely to receive lower priority values, medium-demand sectors have a balanced assignment, and high-demand sectors are more likely to receive higher priority values. This ensures that sectors with greater demand are generally prioritized for resource allocation while not ignoring other factors that might influence prioritization. Meanwhile, the risk score β_j is assigned independently, using a uniform random selection from predefined values $\{0.25, 0.5, 0.75, 1\}$, introducing variability in risk assessment across sectors. This approach maintains a structured assignment of priority and risk while potentially reflecting the variety present in real-world decision-making.

Region	Sector	D_j
Antakya	Narlıca	429
	Serinyol	423
	Odabaşı	417
	Akasya	410
	Ekinci	400
	Saraykent	358
	Güzelburç	223
	Küçükdalyan	221
	Ürgenpaşa	218
	Kuzeytepe	170
	Akevler	162
	Maşuklu	154
Defne	Çekmece	797
	Harbiye	667
	Sümerler	298
	Dursunlu	212
	Armutlu	197
	Turunçlu	181
	Subaşı	131
	Aşağıokçular	129
	Elektrik	115
	Gümüşgöze	107
	Akdeniz	104

Region	Sector	D_j
Reyhanlı	Yeni	210
	Bağlar	109
	Bahçelievler	117
	Kurtuluş	91
	Esentepe	73
Samandağ	Atatürk	170
	Tekebaşı	165
	Sutaşı	110
	Çiğdede	56
	Kuşalanı	70
Erzin	Cumhuriyet	102
	Hürriyet	73
	İstiklal	65
	İsali	30
İskenderun	Akarca	330
	Akçay	210
	Azganlık	175
	Barbaros	50
	Bekbele	65
	Barıştepe	102
	Gültepe	200
	Gürsel	190

Table 6.1: Regions, Sectors, and Their Demand Values (D_j)

6.2 Computational Results for the Deterministic Model

The optimization model seeks to allocate squads and equipment in a manner that maximizes operational efficiency by ensuring that each sector receives the most effective combination of teams and equipment. Using the prepared dataset, we consider the standard two-region setting with fixed sectoral demands (as provided in Table 6.1), 12 available squads, and 44 total equipment. The model determines the assignment of squads to regions and subsequently schedules equipment operations at the sector level. Since squads are assumed to be identical, the model does not include individual squad-to-sector assignment decisions, which leads to a reduction in the dimensionality of equipment scheduling variables. The resulting region-level squad assignments are presented in Table 6.2, while the post-assignment equipment scheduling and total work completed over time in the Antakya region are detailed in Table 6.3.

Squad	Region
I1	Antakya
I2	Antakya
I3	Antakya
I4	Antakya
I5	Defne
I6	Defne
I7	Antakya
I8	Defne
I9	Antakya
I10	Antakya
I11	Antakya
I12	Defne

Table 6.2: Squad Assignments to Regions

Sector	Time Unit Range	Total Work
Akevler	0–12	159.0
Akasya	0–12	195.0
Ekinci	0–12	292.0
Güzelburç	0–12	18.0
Küçükdalyan	4–12	137.0
Kuzeytepe	0–11	180.0
Narlıca	0–12	254.0
Odabaşı	12	5.0
Serinyol	0–12	423.0

Table 6.3: Work Schedule and Effort by Sector in Antakya Region

In the deterministic run, only 9 out of 12 sectors in the Antakya region were accessed within the 13-hour search and rescue time frame. Several sectors could not be fully covered, leaving a portion of the required workload unaddressed and to be completed by other organizations or later phases of the operation.

Squad assignments across regions appear to be influenced primarily by the type of equipment available to each squad. The equipment-specific boost factor plays a significant role in determining both sector-level assignments and the overall effectiveness of the response. This explains why, although many sectors were worked for similar durations, some achieved higher total work completion. In those cases, the assigned squads possessed a larger number of more suitable equipment types, resulting in greater productivity within the same time frame.

The computational results of the deterministic search and rescue assignment and scheduling model, under varying problem parameters—including different demand scenarios, team sizes, and total equipment availability—are presented in Table 6.4. Demand scenarios are categorized as *Low*, *Average*, and *High*. The *Low* demand scenario is generated by multiplying the sectoral demand values in Table 6.1 by 0.6, while the *High* scenario is obtained by multiplying each sector's demand by 2. The *Average* scenario corresponds to the baseline demand values in the table. This scaling approach enables experimentation across different earthquake magnitudes while preserving the relative distribution of demand across sectors. The scaling factors used to generate the *Low* ($\times 0.6$) and *High* ($\times 2$) demand scenarios are chosen to reflect plausible variation in earthquake severity while maintaining the spatial distribution of demand. The factor of 0.6 simulates a moderate-impact event where infrastructure is partially affected, resulting in reduced search and rescue (SAR) needs. In contrast, the factor of 2 represents a severe event, such as a high-magnitude earthquake and several secondary hazards (e.g., aftershocks, fires).

Scenario			2 Regions		4 Regions		6 Regions	
Demand	Teams	Equipment	Objective	Time(s)	Objective	Time(s)	Objective	Time(s)
Low	8	28	55228.6	1.2139	55228.6	4.569	55445.6	8.651
Low	8	36	68176.6	3.22	68176.6	4.365	68176.6	10.1924
Low	8	44	74357.6	4.329	74364.5	5.987	74364.5	12.214
Low	12	28	62193.5	0.576	63600.5	1.283	63600.5	1.886
Low	12	36	70238.9	0.768	71118.6	3.17	71485.9	7.7255
Low	12	44	83343.9	0.979	84286.3	4.01	84909.5	9.5872
Low	16	28	59539.4	0.5909	59894.1	0.99	60365.8	1.734
Low	16	36	74298.5	0.433	75843.1	1.046	76809.1	2.219
Low	16	44	82188.1	0.471	85125.6	2.3821	86395.8	4.7473
Avg	8	28	59922.0	0.326	61623.2	1.096	62013.2	1.226
Avg	8	36	76082.0	0.4807	76082.0	0.998	76082.0	2.099
Avg	8	44	82204.5	2.223	84328.5	3.258	84328.5	5.586
Avg	12	28	67506.8	0.355	70045.8	0.459	70045.8	0.6294
Avg	12	36	77995.2	0.3047	79927.2	0.518	79927.2	0.667
Avg	12	44	93246.0	0.824	95864.8	4.215	95864.8	5.119
Avg	16	28	64200.8	0.343	66720.0	0.356	67110.0	0.486
Avg	16	36	81320.0	0.404	84025.0	0.4014	84610.0	0.538
Avg	16	44	92339.0	0.269	96099.2	0.5714	96912.8	0.7346
High	8	28	68270.8	0.381	70237.5	0.331	70237.5	0.467
High	8	36	85891.5	0.2673	85891.5	0.3785	85891.5	0.487
High	8	44	97093.0	0.474	97093.0	1.192	97093.0	1.7107
High	12	28	75847.5	0.246	76237.5	0.331	76302.5	0.470
High	12	36	89884.8	0.244	89884.8	0.395	89884.8	0.543
High	12	44	109240.0	0.2723	109792.0	0.839	109792.0	1.2801
High	16	28	72217.5	0.485	72735.0	0.66	72735.0	0.4063
High	16	36	93162.0	0.3457	94177.5	0.7760	94177.5	1.0086
High	16	44	106418.0	0.4457	107700.0	0.611	108480.0	0.712

Table 6.4: Optimization results for different region counts, demand levels, teams, and equipment.

Note: Computational results shown in this study were made under the assumption that the binary constraint on the variable x_{jtk} could be relaxed without changing the optimal objective value, which has later been proven incorrect. Currently, new computational results are being obtained without this assumption, and the objective value results shown here can be interpreted as a close upper bound for the original problem. A snippet of results of the unrelaxed model is demonstrated in Table 6.5.

Scenario			2 Regions		4 Regions		6 Regions	
Demand	Teams	Equipment	Objective	Time(s)	Objective	Time(s)	Objective	Time(s)
High	8	28	68266.2	0.462	70237.5	0.324	70237.5	0.443
High	8	36	85891.5	0.257	85891.5	0.356	85891.5	0.475
High	8	44	97093.0	0.429	97093.0	1.378	97093.0	2.070
High	12	28	75847.5	0.237	76237.5	0.324	76302.5	0.455
High	12	36	89878.8	0.277	89882.5	0.644	89878.8	0.531
High	12	44	109224.0	0.340	109776.0	1.049	109772.0	1.548
High	16	28	72217.5	0.502	72735.0	0.329	72735.0	0.686
High	16	36	93146.2	0.375	94177.5	0.795	94177.5	1.026
High	16	44	106401.0	0.568	107700.0	0.596	108480.0	0.720

Table 6.5: Optimal objective values and computational times of models with x variable constrained to binary domain

In the deterministic model, it is assumed that equipment performs the actual work, while the number of squads present in a region determines how equipment is distributed and utilized simultaneously across sectors. Intuitively, one might expect that increasing the number of squads would enhance the overall objective function value. However, when all other parameters remain unchanged, we observe little improvement and, in some cases, even a reduction in the optimal objective function value.

This phenomenon can be attributed to two key factors. First, since the total number of available equipment remains fixed as a parameter, increasing the number of squads only affects the spatial flexibility of equipment usage without necessarily increasing the total work completed per time unit. In other words, additional squads can facilitate equipment distribution across sectors but do not inherently boost productivity, as another squad could have utilized the same set of equipment. This explains why the increase in the objective function value with additional squads is insignificant.

Second, the occasional decrease in the objective function value as the number of squads increases can be attributed to the redistribution of equipment among squads. A change in squad-equipment assignments may lead to suboptimal squad-region matches, resulting in a slightly less effective allocation compared to configurations with fewer squads. While this outcome may seem counterintuitive—since more squads might be expected to enhance potential work—squads with few number of equipment contribute little to search and rescue operations. In real-world scenarios, additional squads typically arrive with their own equipment, ensuring that their presence improves overall effectiveness. Moreover, when squad-equipment assignments are predefined rather than optimized within the model, the mere presence of additional squads without an increase in the total number of equipment does not necessarily translate to a more efficient search and rescue process.

The computational time of the optimization model is influenced by both problem complexity and the gap between the potential work capacity and the required work. As expected, increasing the number of regions leads to higher computational times due to the increased problem complexity.

When comparing computational times across scenarios with the same number of regions, we observe that lower-demand settings generally require more computational time. This is primarily because, in these cases, the potential amount of work that can be performed is relatively close to the total required work, leading to a more intricate allocation process. In contrast, in higher-demand settings, the model has clearer priorities for allocating resources, resulting in comparatively faster solution times.

6.3 Computational Results for the α-Reliable Mean Excess Regret Model

While the minimax regret model introduced in this study provides protection against the worst-case scenario, it did not meet the desired computational time requirements in initial experiments. As a result, the α-reliable mean excess regret model was adopted as a more computationally efficient alternative. The remainder of the experiments and results presented in this study are based on this formulation, and minimax regret computations were not pursued further.

For the stochastic test instances, we use the average demand (1.0×) as the baseline and apply demand multipliers drawn from an arbitrary distribution. Specifically, we sample from a truncated normal distribution with a mean of 1, a standard deviation of 0.5, and bounds of 0.5 and 2.5. Each sampled multiplier is applied to the average demand values presented in Table 2 to generate scenario-specific demand values.

The remaining stochastic problem parameters, including team and equipment availability, are fixed at 12 teams and 36 pieces of equipment. The boost factor assignment process remains identical to the deterministic setting, with fixed values across all scenarios. However, priority and risk scores are re-randomized based on sectoral demand in each scenario. As a result, in high-demand scenarios, priority scores are expected to be higher, while in low-demand scenarios, priority scores tend to be lower compared to the average demand case.

For each stochastic α-reliable mean excess regret problem, we first generate the scenario data, where demand, priority, and risk scores vary across scenarios, while all other parameters remain fixed. Once all scenario parameters are generated, we solve the deterministic version of each scenario to obtain the optimal objective value (μ^*_ω), which is then used in the mean excess regret model. As shown in constraint (14), the mean excess regret model incorporates these deterministic optimal values. Finally, we construct and solve the mean excess regret model for test instances with varying numbers of scenarios: 5, 10, 20, 30, 40, 50, 60, 70, 80, 90, and 100, across the 2-region, 4-region, and 6-region settings introduced in the deterministic computations.

The α-reliable mean excess regret model incorporates the probability of each scenario occurring as a parameter. Since scenario parameters are generated through randomization, we assume that all scenarios have an equal probability of occurring, ensuring a uniform representation of uncertainty without compromising randomness.

Computational results indicate that instances with fewer scenarios are solved more quickly than those with a larger number of scenarios. Additionally, increasing scenario complexity—particularly in terms of the number of sectors—results in longer computation times. Furthermore, objective value deviations are lower among models with a higher number of scenarios, whereas lower-scenario models exhibit greater variability. This suggests that as the number of scenarios increases, the model better captures the underlying distributional behavior, leading to more stable and representative results. Given that the sampling process generates only a limited number of scenarios, an infinite number of scenarios would theoretically provide a complete representation of the demand distribution, fully embedding its characteristics into the optimization framework.

Scenario	**2 Regions**		**4 Regions**		**6 Regions**	
	Obj	Time(s)	Obj	Time(s)	Obj	Time(s)
5	1029.5	7.18	1781.0	45.87	1170.0	44.40
10	1029.5	10.79	2019.0	243.65	1950.0	267.16
20	985.5	48.29	2153.37	821.58	2006.75	1128.2
30	963.833	186.87	2173.25	1799.85	2022.25	1940.41
40	979.25	385.60	2167.94	2352.78	2011.12	2672.55
50	977.95	389.35	2191.75	3989.05	2038.70	4089.48
60	997.375	559.18	2188.67	5431.50	2030.67	3886.53
70	991.714	464.30	2187.14	5087.33	2034.14	5392.88
80	985.438	969.63	2235.72	5582.52	2027.09	5959.24
90	982.11	1226.53	2222.41	9824.51	2024.36	6740.45
100	977.7	1125.20	2231.46	9554.40	2030.12	8909.00

Table 6.6: Objective values and computation times across different scenarios for 2, 4, and 6 regions.

6.4 Heuristic Algorithm

To facilitate the identification of high-quality solutions for the stochastic α-reliable mean excess regret search and rescue problem, we propose a heuristic algorithm that leverages iterative sampling and warm-starting. Given a target model with m_2 scenarios, the heuristic begins by repeatedly solving smaller subproblems composed of m_1 scenarios, where $m_1 \ll m_2$, over n independent iterations. As solving the full m_2-scenario problem is computationally intensive, this approach allows for efficient exploration of the solution space using tractable subproblems.

First-stage decisions—i.e., squad-to-region assignments made before the realization of uncertainty—obtained from the m_1-scenario models are fed into the larger m_2-scenario model. Once these first-stage decisions are fixed, the m_2 model becomes decomposable into smaller deterministic subproblems by region and scenario. Given the fixed assignments, the solver can quickly identify the optimal solution to each subproblem. Optimal solutions to each subproblem then combined to construct a feasible solution for the m_2-scenario model. The solution obtained in this manner, using the best first-stage decision set from iterative m_1-scenario runs, typically serves as a high-quality estimate for the optimal solution of the full m_2-scenario model.

Algorithm 1 Iterative Sampling and Warm-Start Heuristic for the α-Reliable MER SAR Problem

Input: Number of small-scenario iterations n, subproblem size m_1, full model size m_2
Initialize: `best_obj` $\leftarrow +\infty$, `Y` $\leftarrow \emptyset$
for each iteration $i = 1$ to n **do**
    Randomly generate an m_1-scenario instance
    Solve the m_1-scenario model to optimality and extract first-stage decisions y
    if $y \notin$ `Y` **then**
        Add y to `Y`
        Fix y in the m_2-scenario model as first-stage decisions
        Construct $|\Omega| \times |N|$ deterministic subproblems for each region $n \in N$ and scenario $\omega \in \Omega$
        Solve all deterministic subproblems and combine their solutions into a feasible solution `sol`
        Evaluate the objective value `obj` of `sol` in the m_2-scenario model
        if `obj` $<$ `best_obj` **then**
            `best_obj` $\leftarrow$ `obj`
            `best_sol` $\leftarrow$ `sol`
        end if
    end if
end for
Warm-start phase:
Initialize the full m_2-scenario model with variable values from `best_sol`
Solve the m_2-scenario model to optimality

However, in certain cases—particularly under high problem complexity—these heuristic solutions may exhibit undesirably high deviations from the optimal objective. To mitigate this risk, the algorithm evaluates the performance of each candidate solution by feeding it into the full m_2-scenario model and measuring the resulting objective value deviation.

For increased reliability in complex instances, we introduce a second stage to the heuristic. Rather than accepting the best-performing solution obtained from the heuristic as the final solution, we use it to warm-start the full m_2-scenario model. This warm-starting strategy is designed to accelerate convergence and reduce total computational time required to reach optimality or near-optimality in the full-scale problem.

To evaluate the performance of the proposed heuristic, we apply it to test instances structurally similar to those used in the mean excess regret experiments. Specifically, we test the algorithm on instances with 60, 70, and 80 scenarios under varying levels of complexity corresponding to the 2-, 4-, and 6-region problem settings.

Observations from the computational experiments are summarized in Table 6.7. The results indicate that the heuristic algorithm successfully identified optimal solutions in most instances, particularly in problems with fewer scenarios. As the complexity of the problem increases—either through a higher number of regions or scenarios—the heuristic solutions begin to deviate from the optimal, highlighting the growing challenge of maintaining solution quality under increased dimensionality.

The second stage of the heuristic, which incorporates a warm-start strategy, demonstrates notable improvements in computational efficiency for a majority of the instances.

The most substantial gains are observed in the 4-region, 80-scenario setting, where time savings range between 66.83% and 80.85%. However, there are instances in which the warm-start procedure does not yield improvements. Specifically, the 6-region, 60-scenario and 2-region, 70-scenario cases exhibit the lowest average performance gains, while the 6-region, 80-scenario instance shows no improvement at all. This is likely due to increased model complexity leading to memory overuse, which adversely affects warm-start performance.

Notably, the heuristic combined with warm-start yields the greatest average computational improvement when using the smallest heuristic configuration—namely, 3 iterations with 5 scenarios ($m_1 = 5$). This suggests that high-quality solutions for warm-starting the full model can generally be identified using small-scale subproblems and a limited number of iterations. Since the computational time required by the warm-start process is approximately constant across instances with the same number of regions and scenarios (and ideally invariant when the same solution is used), minimizing the number of heuristic trials is crucial for maximizing time efficiency.

It is also observed that the number of unique solutions generated by the heuristic increases with problem complexity, indicating greater variability in the solution space. This justifies the use of additional heuristic iterations in more complex instances, as suboptimal heuristic solutions can lead to significant deviations from the optimal objective, particularly evident in the 6-region, 60- and 70-scenario models.

Overall, the heuristic algorithm is capable of generating optimal or near-optimal solutions in significantly less time than the original model. When combined with the warm-start strategy, it further enhances performance by accelerating convergence to the optimal solution. These results demonstrate the effectiveness of the proposed algorithm in improving the solution process for the mean excess regret model, especially when the problem complexity remains within manageable bounds.

Region	m_2	Iterations	m_1	Model Time(s)	Heuristic Time(s)	Warmstart Time(s)	Algorithm Total	Time Saved	Model Obj	Heuristic Obj	Devitation(%)	Unique
		3	5	969.63	79.64	429.60	509.24	47.48%	985.44	985.44	0	1
		3	10	969.63	102.85	440.61	543.46	43.95%	985.44	985.44	0	1
2	80	5	5	969.63	111.67	474.83	586.50	39.51%	985.44	985.44	0	2
		5	10	969.63	136.09	387.83	523.92	45.97%	985.44	985.44	0	1
		10	5	969.63	149.74	385.83	535.57	44.77%	985.44	985.44	0	2
		3	5	464.303	73.22	311.87	385.09	17.06%	991.71	991.71	0	1
		3	10	464.303	130.90	307.12	438.02	5.66%	991.71	991.71	0	2
2	70	5	5	464.303	79.17	304.15	383.32	17.44%	991.71	991.71	0	2
		5	10	464.303	138.40	278.92	417.32	10.12%	991.71	991.71	0	2
		10	5	464.303	118.59	283.59	402.18	13.38%	991.71	991.71	0	2
		3	5	559.18	57.52	227.07	284.59	49.11%	997.38	997.38	0	1
		3	10	559.18	103.29	222.18	325.47	41.80%	997.38	997.38	0	2
2	60	5	5	559.18	76.47	248.91	325.38	41.81%	997.38	997.38	0	1
		5	10	559.18	144.60	245.87	390.47	30.17%	997.38	997.38	0	2
		10	5	559.18	138.12	237.72	375.84	32.79%	997.38	997.38	0	2
		3	5	13079.04	266.91	2238.03	2504.94	80.85%	1759.84	1859.28	5.35	2
		3	10	13079.04	674.74	3024.13	3698.87	71.72%	1759.84	1759.88	0.002	2
4	80	5	5	13079.04	380.48	2247.76	2628.24	79.90%	1759.84	1859.28	5.35	2
		5	10	13079.04	1303.82	3034.52	4338.34	66.83%	1759.84	1759.88	0.002	4
		10	5	13079.04	729.86	3005.95	3735.81	71.44%	1759.84	1759.88	0.002	4
		3	5	5337.27	277.17	1633.65	1910.82	64.20%	1740.52	1891.75	8	3
		3	10	5337.27	775.17	3065.58	3840.75	28.04%	1740.52	1740.52	0	2
4	70	5	5	5337.27	306.73	3625.21	3931.94	26.33%	1740.52	1740.52	0	2
		5	10	5337.27	1025.68	3878.79	4904.47	8.11%	1740.52	1891.75	8	3
		10	5	5337.27	421.71	2959.92	3381.63	36.64%	1740.52	1740.52	0	3
		3	5	6352.7	255.34	3467.1	3722.44	41.40%	1746.61	1881.38	7.16	1
		3	10	6352.7	661.44	4514.07	5175.51	18.53%	1746.61	1746.61	0	2
4	60	5	5	6352.7	315.72	2597.83	2913.55	54.14%	1746.61	1746.61	0	3
		5	10	6352.7	963.76	4019.28	4983.04	21.56%	1746.61	1746.61	0	2
		10	5	6352.7	610.70	4016.21	4626.91	27.17%	1746.61	1746.61	0	4
		3	5	15256	639.61	16747.19	17386.8	None	1944.38	1981.08	1.85	2
		3	10	15256	2517.88	14331.04	16848.92	None	1944.38	1944.85	0.024	2
6	80	5	5	15256	711.92	15439.48	16151.4	None	1944.38	1981.08	1.85	3
		5	10	15256	2899.69	14309.73	17209.42	None	1944.38	1944.85	0.024	2
		10	5	15256	1107.06	14309.78	15416.84	None	1944.38	1944.85	0.024	4
		3	5	9396.65	590.86	5342.78	5933.64	36.85%	1887.34	1997.39	5.5	2
		3	10	9396.65	1479.23	5257.39	6736.62	28.31%	1887.34	1887.84	0.026	2
6	70	5	5	9396.65	926.14	5410.23	6336.37	32.57%	1887.34	1997.39	5.5	3
		5	10	9396.65	4259.93	5209.78	6278.90	33.18%	1887.34	1887.84	0.026	2
		10	5	9396.65	1198.48	5789.90	6988.38	25.63%	1887.34	1997.39	5.5	3
		3	5	7373.466	648.23	5607.36	6255.59	7.33%	1908.19	2004.63	4.81	2
		3	10	7373.466	2795.35	5621.18	6672.34	4.60%	1908.19	2004.63	4.81	2
6	60	5	5	7373.466	965.51	5542.14	6507.65	5.68%	1908.19	1908.77	0.03	3
		5	10	7373.466	4326.54	5579.64	6890.32	3.17%	1908.19	1908.77	0.03	3
		10	5	7373.466	1743.27	5678.90	7002.46	2.43%	1908.19	1908.77	0.03	6

Table 6.7: Heuristic Algorithm and Warmstart Results

Chapter 7

Conclusion and Future Work

This study first examined three of the most destructive earthquakes in Türkiye's recent history—the 1999 İzmit, 2011 Van, and 2023 Kahramanmaraş earthquakes—with a focus on the human toll, scale of destruction, and operational challenges faced during the immediate post-disaster period. Analysis of these cases revealed recurring structural weaknesses in Türkiye's search and rescue (SAR) response, including delayed mobilization, poor inter-agency coordination, insufficient equipment capacity, and gaps in communication infrastructure. These deficiencies often resulted in slower rescues and higher mortality within the critical time window, starting immediately after the disaster. The need for risk-sensitive, resource-efficient, and spatially aware planning tools in SAR logistics wab observed during these past shortcomings.

In recent years, Türkiye has reportedly made considerable strides in enhancing its disaster response capacity. Technological upgrades in communication systems, expansion of equipment inventories, and better training for professional SAR teams, such as those managed by AFAD and major municipal firefighting departments, can be counted as meaningful improvements. For instance, the structured deployment of SAR equipment bags, increased aerial reconnaissance capability, and readiness drills in urban centers like Istanbul suggest a shift toward more rapid and better-coordinated operations. This study aims to complement those developments by introducing an optimization-based decision support framework to further strengthen SAR resource allocation and scheduling processes during the early response phase.

The main goal of this study is to provide an optimization-based decision support framework for post-earthquake search and rescue (SAR) operations, addressing both deterministic and stochastic formulations of the squad assignment and scheduling problem. The deterministic model captures operational realities based on data collected from SAR institutions in Turkey, incorporating sector-level workload, equipment availability, and regional assignments. To handle demand uncertainty, we extend the model to a stochastic setting using minimax regret and α-reliable Mean Excess Regret (α-MER) formulations, which provide a risk-aware objective that balances efficiency and robustness in the face of uncertain disaster environments. We then continue our computational experiment with (α-MER)formulation as it demonstrated domination in initial experimentation phase of the study.

A key contribution of this work lies in the integration of scenario-based stochastic modeling with a regret minimization framework that is operationally interpretable and computationally tractable. We generate scenario-specific demand, priority, and risk profiles using samples from arbitrary distributions and examine the impact of varying region counts and scenario sizes on solution quality and computational time. The results confirm the effectiveness of α-reliable MER in producing stable solutions under increasing uncertainty.

To further address scalability concerns, we propose a two-stage heuristic algorithm that iteratively samples smaller subproblems and uses the best-performing solutions to warm-start the full-scale model. Computational experiments demonstrate that this heuristic is capable of producing optimal or near-optimal solutions with significant reductions in total computation time. The warm-start strategy, in particular, proves beneficial in complex instances, with time savings reaching over 50% in some settings.

Despite the improvements achieved, certain limitations persist. In particular, the performance of the heuristic declines in high-dimensional cases involving many regions and scenarios, occasionally offering no computational advantage. These findings underscore the importance of balancing model complexity with available computational resources and point to the potential value of hybrid metaheuristic or decomposition-based approaches.

Future research can extend this work along several dimensions. First, the performance of the heuristic and warm-start algorithm can be further evaluated on alternative datasets and under varying configurations, particularly focusing on smaller values of m_1 and iteration counts to better understand the trade-off between computational cost and solution quality. Future computational experiments may be conducted using alternative datasets—either simulated or derived from real-world disaster scenarios—to further enhance the realism and applicability of the proposed modeling framework. Second, the stochastic model can be enhanced by modifying the information structure so that uncertainty is revealed upon a squad's arrival at a sector, rather than after all squad-region assignments have been made. This would more accurately reflect the operational realities of post-disaster environments. Third, a variant of the model could be developed to limit or prohibit equipment sharing between teams during discrete time units, capturing logistical or operational constraints observed in practice. Finally, the model can be extended to account for individual team-level assignment decisions by incorporating skill-based matching between squads and sectors or equipment types, introducing a richer layer of personnel-resource compatibility into the optimization framework.

Although it is not feasible to carry out real-time computational scheduling and assignment of search and rescue squads and equipment during an actual post-earthquake event, the models developed in this study provide valuable insights into the effectiveness and trade-offs of different allocation strategies. These insights, obtained through computational experimentation, can inform and potentially enhance existing methodologies used by disaster response authorities. To this end, it is essential to construct mathematical models that reflect the operational realities of post-disaster environments, including uncertainty, logistical constraints, and time sensitivity. By doing so, these models can serve as a foundation for developing practical, data-driven strategies to support post-earthquake SAR efforts. A promising direction for future research is the design of implementable SAR strategies that balance computational efficiency and real-world applicability within the disaster zone.

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Appendices

Appendix A

Search and Rescue Equipment Bags

Box 3: Pneumatic Lifting Bag Set

- Holmatro Air Lifting Bag – HLB 40 (2 pcs)
- Holmatro Air Lifting Bag – HLB 24
- Holmatro Air Lifting Bag – HLB 29
- Holmatro Air Lifting Bag – HLB 18
- Inflation Cylinder
- Inflation Kit and Hose (inside the case)

Figure A.1: Box 3: Pneumatic Lifting Bag Set

Box 4: Hydraulic Spreader and Hose Kit

- Holmatro Hydraulic Spreader – SP4241C
- Holmatro Hydraulic Pressure Hose

Figure A.2: Box 4: Hydraulic Spreader and Hose Kit

Box 6: Hydraulic Ram and Accessories Kit

- Holmatro Manual Hydraulic Power Unit
- Holmatro T Ram – RA 4332 C
- Holmatro Telescopic Ram – TR 4340 C
- Ram Support Holmatro – HRS 22
- Ram Extension (Short)
- Ram Extension (Long)

Figure A.3: Box 6: Hydraulic Ram and Accessories Kit

Box 7: Concrete and Tree Cutting Kit

- Gasoline Concrete Cutter – Wacker BTS1035
- Concrete Cutting Blades (3 pieces)
- Concrete Cutter Maintenance Tool (Orange Bag)
- Tree Cutter Maintenance Tool (Orange Bag)
- Gasoline Tree Cutter – Dolmar PS7300
- Tree Cutter Spare Chain
- Tree Cutter Spare Blade
- Gasoline Canister (6 liters)
- Spare Oil

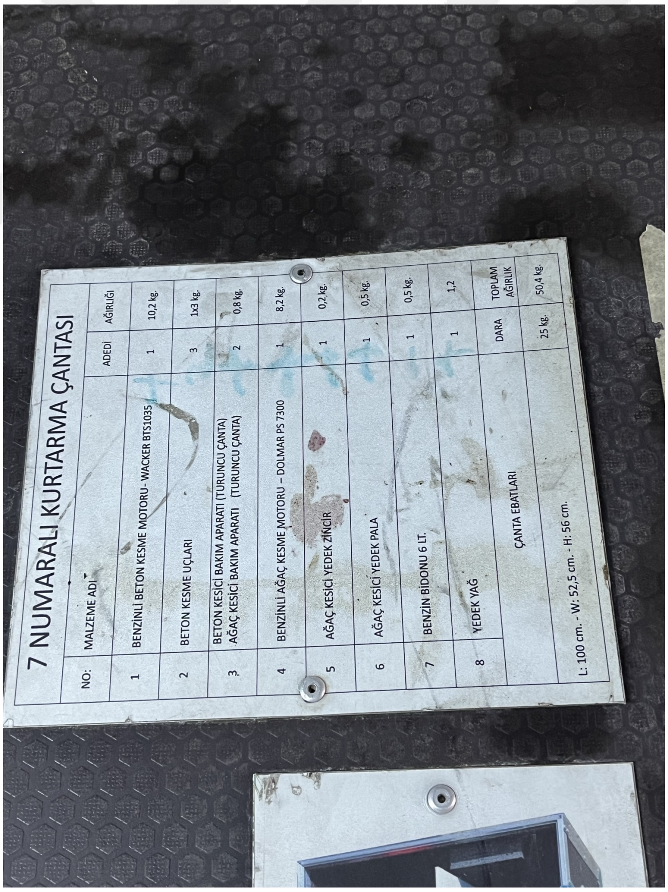

Figure A.4: Box 7: Concrete and Tree Cutting Kit

Box 8: Lighting and Saw Kit

- Lighting Tripod
- Floodlight – 1000W
- 50-meter Reel Extension Cable
- Reciprocating Saw – Bosch
- Dual Floodlight Stand
- Spare Bulbs (3 pcs)
- Tripod Stabilization Rope and Stakes (3 pcs)

Figure A.5: Box 8: Lighting and Saw Kit

Box 9: Hydraulic Cutter and Spreader Kit

- Holmatro Hydraulic Cutter – CU 4030
- Holmatro Hydraulic Pressure Hose
- Holmatro Spreader – CL 4007

Figure A.6: Box 9: Hydraulic Cutter and Spreader Kit

Box 10: Gasoline Hammer Drill Kit

- Gasoline Hammer Drill – Wacker
- Chisel Tip for Hammer Drill

Figure A.7: Box 10: Gasoline Hammer Drill Kit

Box 12: Adjustable Ground Support Ends

- Adjustable Bar Support Ends (Adaptable to Ground Conditions) – Quantity: 23

Figure A.8: Box 12: Adjustable Ground Support Ends

Box 14: Structural Stabilization Kit

- 20x20 Wooden Blocks
- Holmatro Hydraulic Power Unit (for shoring)
- Bar Stabilization Base
- Mechanical Threaded Shoring Apparatus
- Bar Ends
- Block Attachment Ends
- L-Type Support Ends
- Tensioning Hook
- Tensioning Strap

Figure A.9: Box 14: Structural Stabilization Kit