LOCATION ROUTING MODELS WITH ENERGY CONSUMPTION CONSTRAINTS FOR UAVS FOR MONITORING ILLEGAL MIGRATION FLOW

(KAÇAK GÖÇMEN AKIŞININ İHALAR YARDIMIYLA GÖRÜNTÜLENEBİLMESİ İÇİN ENERJİ KISITLI LOKASYON ROTALAMA MODELLERİ)

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LIST OF SYMBOLS

AFV	: Alternative Fueled Vehicles
ALNS	: Adaptive Large Neighborhood Search
BSS	: Battery Swap Station
EV	: Electrical Vehicle
FEMA	: Federal Emergency Management Agency
GVRP	: Green Vehicle Routing Problem
GVRP-MTPR	: Green Vehicle Routing Problem Multiple Technologies and Partial Recharge
IF	: Intra Route Facilities
LRP	: Location Routing Problem
LRPTW	: Location Routing Problem with Time Windows
MMAS	: Max-Min Ant System
MILP	: Mixed Integer Linear Programming
PwC	: PricewaterhouseCoopers
RVRP	: Recharge Vehicle Routing Problem
SPP	: Shortest Path Problem
TSP	: Travelling Salesman Problem
UAV	: Unmanned Aerial Vehicle
UN	: United Nations
UNHCR	: United Nations Refugee Agency
VNS	: Variable Neighborhood Search
VRP	: Vehicle Routing Problem
VTOL	: Vertical Take-off and Landing
WSN	: Wireless Sensor Network

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ABSTRACT

Unmanned Aerial Vehicles (UAVs) are aircrafts that are guided autonomously, by remote control, or both, and that are equipped with sensors, go-pro cameras, global positioning system (GPS), etc., depending on their purpose of use. Unencumbered by crew and the design-safety requirements of manned aircrafts, UAVs can be efficiently used in a wide range of military, commercial, and civil applications, where the last includes weather monitoring, forest fire detection, traffic control, and emergency search and rescue.

The world has witnessed the biggest number of refugees on record at the end of 2016; an unprecedented 65.6 million people around the world were forced from home by conflict and persecution. Among them, the conflict in Syria was the world's biggest producer of refugees with about 5.5 million refugees. Many of these refugees tried to cross the Mediterranean Sea by overloaded and unsafe boats, and most of these trials ended in tragic ends with sunk boats and drowned people. There are lots of papers that have been written on different aspects of disaster management. None of these, however, have addressed the refugee problem, even though the International Federation of Red Cross and Red Crescent Societies (IFRC) have identified displaced populations as a disaster type.

Our aim in this study is to model and solve a UAVs' surveillance problem. That is, we are given a set of target points that have to be visited once, a set of potential locations where stations to swap batteries or to refuel UAVs can be placed, and a main depot from which UAVs are initially launched and to where they eventually return. All these points form the node set of an undirected graph. We are also given a set of homogeneous UAVs. Now, our problem is to determine which of the potential stations to open and the routes of UAVs

which minimize the total sum of operating costs of UAVs and opening costs of stations under several different sets of constraints. This problem type is known as the Location-Routing (L-R) problem in the OR/MS literature. However, due to the technical properties of UAVs, our mathematical formulation differs from the classic L-R formulation, as explained below. Our contributions to the literature can be explained as follows.

Firstly, we propose the UAVs' surveillance problem as part of the risk mitigation phase of disaster management, where risk mitigation is defined by Federal Emergency Management Agency (FEMA) as the activities taken to prevent a disaster, reduce the chance of it happening, or reduce its damaging effects. We can achieve this by considering all target points to fill the danger area where many refugee boats have sunk so far. By surveying these points continuously, we aim at reducing the risk of boats passing through that area. Secondly, UAVs have very limited battery or fuel capacities. Hence, during their missions, their batteries have to be charged or swapped, or they have to be refueled. Therefore, different from the classic L-R formulation, we consider energy consumptions of UAVs in different flight statuses, and formulate the remaining consumable energies as part of our constraint sets. Moreover, in our problem, each subtour made by an UAV has to start and end at the main depot; hence, we formulate new subtour elimination constraints which eliminate all subtours that do not start and end at the main depot.

ÖZET

İnsansız Hava Araçları (İHAlar) kullanım alanına göre sensörler, kameralar ve küresel konumlama sistemi (GPS) gibi birçok ekipmanla donatılabilen; otonom, uzaktan kontrol veya her ikisi olacak şekilde kumanda edilebilen hava araçlarıdır. Klasik hava araçlarının aksine mürettebat ihtiyacı duymayan ve güvenlik zaafı daha az olan İHAlar askeri, ticari ve hava durumu tahmini, orman yangını tespiti, trafik kontrolü ve arama kurtarma gibi birçok günlük sivil uygulamalarda geniş ve etkili bir şekilde kullanılabilir.

Dünya tarihindeki en büyük göçmen hareketi 2016 yılında kaydedildi. Yaklaşık 65.6 milyon insanın işkence ve çatışmalar yüzünden yurtlarını terk ettiği bu yılda Suriye Savaşı 5.5 milyon göçmenle bu istatistiğe en çok katkı yapan olay oldu. Bu göçmenlerin önemli bir kısmı Akdeniz üzerinden taşıma kapasitesini aşmış ve güvenli olmayan botlarla Avrupa'ya kaçmak istediyse de bu denemelerin birçoğu botların batması ve göçmenlerin ölümüyle sonuçlandı. Afet yönetimi alanında birçok çalışma yapılmış olsa da, göçmenlik durumunun otoritlerce afet olarak tanımlamasına rağmen, bu konu hiçbir çalışmada afet olarak ele alınmamıştır.

Bu çalışmada bizim amacımız önceden belirlenen ve homojen bir İHA filosu yardımıyla bu göçmen akışının görüntülenmesi problemini modellemek ve çözmektir. Problem dahilinde sadece bir kez ziyaret edilecek noktalar, açılması muhtemel batarya değiştirme istasyonları ve İHAların kalkış ve iniş yapacağı ana deponun konumları önceden belirlenmiş ve bu düğümler yönsüz çizge oluşturmaktadır. Problemimiz belli kısıtlar altında operasyon ve istasyon açma maliyetlerini en aza indiren İHA rotalarını ve hangi istasyonların açılacağını belirlemektir. Bu problem yöneylem araştırmaları literatüründe Lokasyon-Rotalama (L-R) problemi olarak bilinmektedir. Fakat bizim sunduğumuz model, İHAların teknik özelliklerinden dolayı klasik L-R modellerinden farklıdır. Çalışmamızın katkıları aşağıdaki gibidir.

Öncelikle, İHAların görüntüleme problemi afet yönetiminin risk azaltma aşamasında tanımlanmıştır. Risk azaltma aşaması bir afet olmadan önce onun olma olasılığının ve/veya olması durumunda vereceği hasarın azaltılmasına yönelik adımlar atılan aşamadır. Bu amaca yönelik olarak kaçak göçmen akışının ve –bunun sonucu olarak- göçmen botlarının battığı rotayı kapsayacak şekilde noktalar atanmıştır. Bu noktalar sürekli olarak veya göçmen akışının en yoğun olduğu saatlerde İHAlar tarafından ziyaret edilerek göçmen akışının gözlenmesi ve oluşabilecek facialarını önlenmesi amaçlanmıştır. İkinci olarak İHAların düşük batarya/yakıt kapasitesi göz önünde bulundurulmuş ve görev dâhilinde bu bataryaların değişmesi veya yakıt ikmali yapılması durumu modele eklenmiştir. Bu bağlamda İHAların her bir uçuş durumu için harcadığı enerji hesaplanmış ve kalan harcanabilir kısıtları L-R modeline eklenerek literatüre kazandırılmıştır. Son olarak, ana depoda başlayıp ana depoda bitmeyen İHA hareketlerini içeren alt turlar, yeni alt tur eleme kısıtlarıyla elenmiştir.

1. INTRODUCTION

Unmanned Aerial Vehicles (UAVs) are the vehicles that can fly without any pilot aboard. They are able to be controlled via remote control with pilot or to move with any controller with pre-defined path (Wen et al., 2018). The first employment of UAVs was for military actions which occur in the hostile territory to reduce pilot losses. With the constant reduction in cost and size, UAVs have become more accessible and valid to apply in daily life in commercial and civilian actions (e.g. weather monitoring, forest fire detection, traffic control, cargo transport, emergency search and rescue etc.).

Even though UAVs differ in many aspects from the operational point of view, they can be classified in two main categories such as fixed-wing and multi-rotor. The comparisons between these two types are given in Table 1.1 (Droneploy, 2017). As it can be seen from the Table 1.1, fixed-wing UAVs are more appropriate to use in military and long-ranged missions while multi-rotor UAVs are easy to fit in civilian applications with their high maneuverability, VTOL (Vertical Take-off and Landing) property and price.

Table 1.1: Comparison of Fixed-wing and Multi-rotor UAVs

Properties\UAV Types	Fixed Wing	Multi-rotor
Maneuverability	Lower	Higher
Price	Higher	Lower
Take-off Area	Requires a path to speed up	VTOL
Payload Capacity	Higher	Lower
Range	Higher	Lower
Stability	Higher	Lower
Ease of use	Lower	Higher
Size	Higher	Lower

The UAVs have become the focus of many studies for over a decade. The researchers investigate ways to increase the number of areas where UAVs are applied because UAVs are easy to use, aren't expensive in both deploying and maintaining when compared with other vehicles, have higher mobility and vertical take-off ability (in VTOL UAVs) (Hayat et al. 2016). The main application areas of UAVs can be divided into two as civilian and military applications. The civilian application studies in the literature can be classified in the following eight categories such as providing wireless coverage, remote sensing, real-time monitoring, search and rescue, delivery of goods, surveillance, precision agriculture, and infrastructure inspection (Shakhatreh et al. 2018). Moreover, military applications are generally arming UAVs to hit some specific targets. Researches in this area are mostly on the infrastructure of UAVs to make them less detectable and increase their precision in target hitting (Boulanin & Verbruggen, 2017).

PwC has published a report (2017) that discusses the commercial UAV market in 2017. In the report, it has been stated that the total addressable market value of UAVs in the global view is above of $127 bn. Another report that has been published by Business Intelligence shows the expectation of UAV sales to reach $12 billion in 2021, which will be caused by consumer UAV shipments, enterprise UAV shipments and governmental usage for surveillance and combat (Joshi, 2017). It is also known that $4.457 billion is budgeted for UAVs in US Department of Defense (Gettinger, 2016).

Humans are migrating from one part of the world to another from the beginning of time. But especially in the last few decades, migration has become more common especially from east to west. The motivations of migrations are classified in two categories which are pull and push motivations. In short, pull motivations are the reasons why you went to place where you migrate to and push motivations are the reasons why you left where you used to locate.

Conflicts, persecution, poverty, unemployment, lack of education, discrimination based on gender or religion, and a general lack of prospects in migrants' countries of origin can be given as examples to push motivations while destination country includes family or friends already there, the possibility of employment and social insurance can be given as examples to pull motivations. In the last decades, illegal immigration has increased steadily especially because of wars and Arab spring (lately). This illegal immigration flows from Middle East or Africa towards Europe or America most generally. The UN Refugee Agency UNHCR publishes reports that indicates illegal migrations in numbers each year. According to these reports 22.5 million refugees are migrated to another country (UNHCR, 2018). In Table 1.2 numbers of illegal migrations toward Europe by seas is given.

Table 1.2: Numbers of Migration Towards EU by Sea

Years	Sea Arrivals	Dead & Missing
2017	172,301	3,139
2016	362,753	5,096
2015	1,015,078	3,771
2014	216,054	3,538

These illegal migrations unfortunately might end up with death of migrants. UNHCR (2018) in their reports also declares demographic qualifications of refugees. According to these reports most of the refugees are male. And Turkey is a country which refugees use as a bridge to Europe.

FRONTEX is found by European Union in 2005 (for the management of operational cooperation at the EU External borders) to detect illegal migration actions (Vytautas, 2016). Due to FRONTEX's report (2015), 1,166 suspected facilitators apprehended and 254,693 people rescued by FRONTEX operation.

In this thesis the UAVs' surveillance problem is analyzed, modeled and solved. That is, given a set of target points which must be visited only once, a set of potential stations where battery swap operations occur, and a main depot from which UAVs take off at the beginning and to which land on at the end of their missions form a node set of an undirected graph, and any two nodes are connected by an edge in this graph. With the given number of homogenous fleet of UAVs, the problem is to determine the locations of the potential stations to open and the routes of UAVs which minimize the total sum of operating costs of UAVs and opening costs of stations under several different sets of constraints. This is a typical Location Routing Problem (LRP). Nevertheless, our mathematical formulation differs from classic LRP formulation, as explained below.

The contributions of this thesis can be expressed as follows. Firstly, we propose the UAVs' surveillance problem as part of the risk mitigation phase of disaster management. This phase is defined by FEMA(year) as the phase where preventive or effect reducing actions are taken to reduce or to prevent the damages of a disaster if it occurs. We can achieve this by considering all target points to fill the danger area where many refugee boats have sunk so far. By surveying these points continuously, we aim at reducing the risk of boats passing through that area.

Secondly, UAVs have very limited battery or fuel capacities. Henceforth, during their missions, their batteries have to be charged or swapped, or they have to be refueled; this is similar to Green VRP problems. Therefore, different from the classical LRP formulation, energy consumptions of UAVs in different flight statuses is considered and the remaining consumable energies are formulated as part of our constraint sets; this consideration differs our problem from the Green VRP problem. Moreover, in the context of the problem each UAV is to start and end their mission at the main depot; hence, new sub-tour elimination constraints to eliminate all sub-tours that do not start and end at the main depot are formulated.

Thirdly, with the consideration of real-life applications, time windows constraints are added to the first formulation to obtain a second formulation, which is LRP with Time Windows (LRPTW) formulation. This addition of the time windows constraints is justified by the fact that most of the danger area has to be surveyed within a time interval. All the contributions are mentioned above holds for LRPTW except the sub-tour elimination constraints. For that formulation, the time windows constraints eliminate all the sub-tours that do not start and end at the main depot.

The rest of the thesis is organized as follows. In Section 2, the relevant literature review is presented in 2 different streams. In Section 3, our novel LRP and LRPTW formulations are introduced with the energy consumption models. In Section 4, the computational study is performed and sensitivities are analyzed for each formulation by changing several parameters. Finally, in the Section 5, the conclusions of the study are presented.

2. LITERATURE REVIEW

In this section the related literature is reviewed in two main streams. The first stream is disaster management and the second stream is routing problem of vehicles.

2.1 Disaster Management

With the increasing number of disasters, disaster management has become one of the most studied research topics among researchers. This topic is different from the other classic topics because it aims to be non-profit, life-saving, and human suffer reducing. Gupta et al. (2016), classifies disasters in two categories as natural and manmade disasters. Manmade disasters include terrorist activities and errors such as industrial errors and transportation errors. Cozzolino (2012) categorizes these operations into four as (1) mitigation, (2) preparation, (3) response and (4) reconstruction. Firstly, Federal Emergency Management Agency (FEMA) (2018) then Altay and Green (2006) defines the phases as follows. Mitigation is the step where preventive actions or effect reducing actions, in case if disaster occurs, are taken. While preparation is the phase that response strategies to be followed when the disaster occurs are determined. Response is defined as the step that actions are taken in order to save lives, properties, and environment and provide continuance to communal structure. As a last step, they define reconstruction (recovery) is the long-term oriented strategies followed to recover community from the instant effects of disasters.

2.1.1 UAV Usage in Disaster Management

The application areas of UAVs are increased with the great progress of the technology. In this subsection, the literature is investigated with the classification made by Erdelj and Natalizio (2016). They distinguish disaster management operations in three categories, w hich UAVs can operationally participate, in their research which investigates UAV usage in disaster management as (1) pre-disaster preparedness, (2) disaster assessment and (3) disaster response and recovery. Henceforth, Erdelj and Natalizio (2016) merged mitigation and preparation phases of disaster management that is classified by Cozzolino (2012).

In the pre-disaster preparedness phase, UAVs usage is limited because of the capacitated operational time of UAVs. Erdelj et al. (2016) recommends using UAVs as an assistant to wireless sensor networks (WSN) in this phase. Ueyama et al. (2014) uses UAVs in order to compensate a fault that is occurred in a node of WSN that is being used to monitor disasters. In this case, researchers run the experiments for flood detection system. Erman et al. (2008) presents data centric routing protocol to compensate WSNs as well.

The other two phases take more attraction than the pre-disaster preparedness phase. In response and recovery phase emergency communication is one of the most crucial parts. The goal of the study is to ensure that the communication system with the rescuers, casualties and disaster managers survives after a disaster occurs. Fu et al. (2015) propose to deploy a Wi-Fi device onto a UAV so that traditional signal range is extended from 100m to 25km. Wu et al. (2018) designed a multi-UAV system to enable communication, with deploying base stations to UAVs. Information gathering is an-other important area of research in order to make effective decisions. Corrado & Panetta (2017), compares the combination of situations where radiation detection, camera vision and GSP information are deployed. They declare that UAV range, data transmission range, UAV`s payload capacity are the biggest challenges.

The routing problems of UAVs in disaster management are going to be discussed in further sections.

2.2. Routing Problem

The problem of routing vehicles (VRP) is one of the best known and practiced research areas in the logistics literature. The problem is to find the optimal routes of a certain number of vehicles to a number of predefined destinations for delivering or collecting purposes. The first VRP study is by Dantzig and Ramser (1959). In the paper, they formulate truck dispatcher problem with the generalization of traveling salesman problem (TSP). In TSP, Hamiltonian path is followed which can be defined as a path that returns to beginning location at the end of the route, all customer nodes are to be visited with objective function of minimizing traveling cost, except some variants.

Feillet et al. (2005), names these variants as “TSP with profits” where the objective function maximizes the profit. TSPs can be categorized in two branches in terms of traveling distance. Matai et al. (2010) classifies TSPs in three categories. The first categorization depends on the equality of distances between every two cities in both directions (symmetric). If the distance or cost of traveling between two cities are equal in opposite directions, the problem is called “symmetric TSP” (STSP) otherwise it is called “asymmetric TSP” (ATSP). The other variant of TSP is called multiple TSP where there is more than one salesman at the depot, which is called as the beginning node.

Dantzig and Ramser (1959) differentiates VRP and TSP as follows: You have q_i demand to be met, P_i nodes to be visited, and a vehicle with a capacity of C. If $C \geq \sum_i qi$, a vehicle can serve all nodes in one trip with a route that links all the nodes. However, if $C \ll \sum_i qi$, the vehicle can’t serve all nodes in one trip. And they underline the condition that number of vehicles to be used doesn’t change this situation. Therefore, the difference can be summarized as the capacity constraint of vehicles in VRP. The difference of routes drawn by using TSP and VRP are given in the Figure 2.1, respectively.

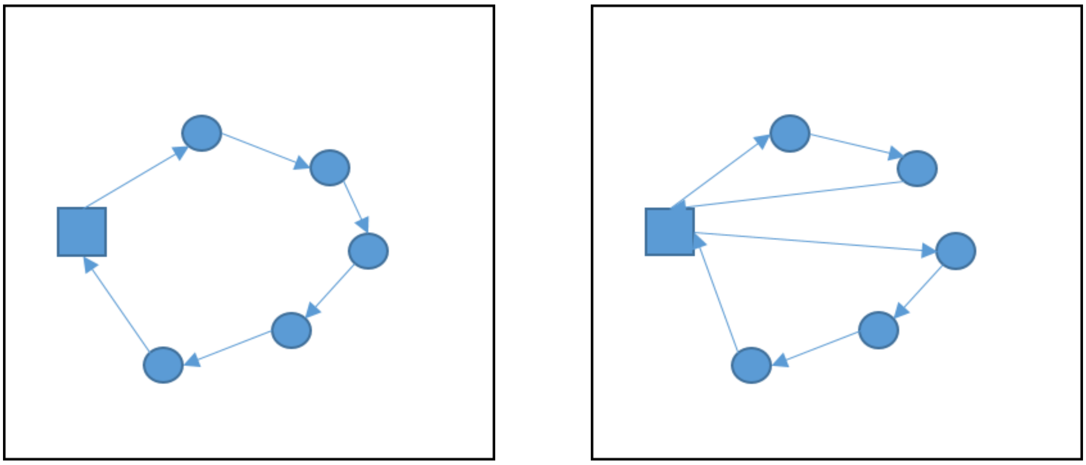

Figure 2.1: Routes of TSP and VRP

2.2.1 Electric Vehicle Routing Problem

The literature of VRP is wide since it is the problem that draws most attention among researchers studying in logistics, transportation and distribution. Therefore, VRP has lots of variants that serve several problems. Electric VRP (EVRP) is a relatively new area that seeks the optimum solution for electric vehicles (EVs) with increasing attention due to advancements in the technology and environmental concerns. Briefly, EVs are the vehicles that have onboard batteries as power sources and have advantages over old fashioned internal combustion engine vehicles in terms of energy consumption and environmental protection. One of the biggest challenges in the problem is the power (limited missiles) limitations of vehicles so while fulfilling the task, vehicles require recharging. Therefore, the recharging action will be taken into consideration with intermediate stops between beginning and destination nodes and the problem is called routing problem with intermediate stops (RPIS); see Schiffer et al. (2019).

Schiffer et al. (2019) differs intermediate stops from regular stops and optional customer stops by defining it as an optional stop to maintain vehicle's operation. And application areas of RPIS is categorized into three as follows: (1) Replenishment and disposal of goods or waste, (2) Refueling and (3) Idling for rest periods and breaks. Here, in this thesis we focus on RPIS for refueling (i.e., swapping batteries).

For internal combustion engine vehicles, the shortest path problem (SPP) is first defined by Ichimori and Ishii (1981) with refueling option at prespecified nodes. They define a time limit (L) which a vehicle can operate without refueling and apply Dijkstra's shortest-path algorithm. The algorithm checks the remaining time of L and decides either going to a refueling node or to a customer.

Conrad and Figliozzi (2011) introduces a new VRP variant with recharging nodes (RVRP) for EVs, which have capacitated range and are able to recharge with constant duration at certain customer stations. The formulation has two objective functions. The first objective is to minimize the number of required vehicles to meet the total demand while the alternative one is to minimize total cost which consists of travelled distance, service time and recharging. The addition of recharging cost into a total cost, recharging action is penalized.

Erdoğan and Miller-Hooks (2012) proposes the formulation that considers recharging stations apart from customers while defining green vehicle routing problem (GVRP) which is a problem that focuses on decreasing carbon emission via alternative fuel vehicles (AFVs) not only electric vehicles (EVs). In the paper, the objective function was to minimize the overall travelled distance, and they declare that the feasibility is subordinate to locations of customers and recharging stations.

Schneider et al. (2014) defines the first formulation that considers EVs explicitly with separate recharging stations from customers while introducing EVRP with Time Windows (EVRP-TW). Dual objective function is employed while the primary objective is to minimize the number of vehicles, the secondary is to minimize total travelled distance with homogenous fleet. The recharging duration is defined as a function of a remaining energy in the battery. Hiermann et al. (2016) extends the formulation with heterogenous fleet of EVs.

Keskin and Çatay (2016) combines EVRP-TW with partial recharging and calls the problem EVRPTW-PR. The problem is formulated as minimization problem that minimizes the total distance traveled. In the paper, all batteries and chargers assumed to have the same performance. Felipe et al (2014) uses four different chargers with different technology and defines the partial recharging for the first time, but they don't consider time windows in their formulation. They extend GVRP with multiple technologies and partial recharges (GVRP-MTPR) with the objective function that minimizes the total cost which consists of recharging cost and traveled distance.

2.2.2 Location Routing Problem

The Location-Routing Problem is a combinatorial problem that seeks for the optimum solution of two widely studied hard problems in the literature which are the location problem of depots, facilities etc. and routing problem of vehicles simultaneously (Prodhon and Prins, 2014). Even though necessity of combining these two problems is declared in 1960s, due to the technological and methodological inadequacies this combination has not accomplished until 1973. Watson-Gandy and Dhorn (1973), published the first paper which combines these two problems. There are lots of variants in the LRP literature, some of these variants are summarized in Table 2.1 (Drexl and Schneider, 2015).

Table 2.1: Main Characteristics in LRP Variants

Characteristics	Types		
Data	Discrete	Stochastic	Fuzzy
Planning Period	Static	Dynamic	Periodic
Locations of Facilities	Discrete	Continuous	Network
Echelons	Single	Multiple	
Objectives	Single	Multiple	
Routings	Vertex	Arc	

Another variant of LRP, which is indicated by Schiffer et al. (2019) in refueling, is Location Routing Problem with Intra-Route Facilities (LRPIF) which differs from classical LRP as regards the type of facility to be located. While the decision of depot location is made in classical LRP, intra-route facility location is decided in LRPIF. These intra-route facilities can be charging station, rest & break point, synchronization etc.

In this context the first research is published by Yang and Sun (2015). Researchers introduces Battery Swap Station Location-Routing Problem with Capacitated Electric Vehicles (BSS-EV-LRP) which is the first time that decision of routes of EVs and locating of battery swap stations are considered simultaneously. In the formulation the minimizing objective function contains BSS construction cost as well as the routing cost of EVs. They only formulate the case that battery is swapped and there is no partial recharging or fully recharging of EVs. Hof et al. (2017) applied enlarged Variable Neighborhood Search (VNS) and obtained better solution than Yang and Sun (2015).

Schiffer and Walther (2017a) extends the BSS-EV-LRP with addition of time windows and partial recharging and introduces electric LRP with time windows and partial recharging (ELRPTWPR). In the study, formulation is discussed for 5 different objective functions that minimizes (i) total traveled distance, (ii) the number of vehicles, (iii) the number of charging stations, (iv) the convex combination of the number of vehicles and the number of charging stations and (v) overall total cost that includes construction of charge stations, total traveled distance and investment to the vehicles. And the results highlight the benefits of making simultaneous decision on routing and location. Schiffer et al. (2017b) applied methodology to a company in retail logistics and examined the competitiveness of EVs for mid-haul fleet. Results showed that EVs are advantageous over conventional vehicles in terms of costs and emissions. Schiffer and Walther (2018) accounts for uncertainties such as costumer demands, and construct robust ELRPTWPR.

Schiffer et al. (2018) construct a new LRPIF with intra-route facilities where vehicles can both recharge and replenish their freight simultaneously. These authors introduce an Adaptive Large Neighborhood Search (ALNS) that outperforms all algorithms mentioned previously.

2.3 UAV Routing Problem and Its Applications in Disaster Management

In logistics of disaster management and surveillance, the routing problem of UAV's is located in the focus point of most works. Chowdhury et al. (2017) proposes a continuous approximation model in disaster response and relief operations for UAVs where they decide for distribution center locations, their service regions, and ordering quantities to minimize overall distribution cost. They include energy usage in model as constant for different movements and do not consider cost of battery.

Rabta et al. (2018) stresses the importance of energy consumption function in models and having recharge stations. They prioritize target points according to emergency level and formed a convex model that the global optimum is guaranteed. Chowdhury (2018) used heterogeneous fleet in order to inspect post-disaster effects.

Kim & Lim (2018) apply electrificated line battery charging for UAVs that have a border surveillance duty. They use 3 different types of UAVs and installed the line for 6 km. Case study is showing that with these specific instruments after 25th flight, electrification line pays back.

Waharte & Trigoni (2010) proposed an algorithm to search and rescue mission with employing and comparing different search strategies which are based on greedy heuristics, potential-based algorithms and partially observable Markov Decision Process to control several UAVs with criteria of the time to reach victim.

Yakıcı (2016), studied the LRP of a fixed number of UAV fleet. In the study, the author limited the flight time deterministically without mentioning any fuel constraint. The problem is formulated as a prize collection Mixed Integer Linear Programming (MILP) problem. When the size of the problem is bigger, the optimum solution cannot be found by a commercial software so that a heuristic approach is developed and applied, which is based on ant colony optimization algorithm.

Yılmaz et al. (2018) considered homogeneous fleet in order to maximize total of importance values collected form interest points with spatio-temporal synchronization constraints (prize collection problem). But this time, they used ships as a refuel platforms that have a limited capacity for recharging. At the end, the comparison of Max-Min Ant System (MMAS) based heuristic with commercial heuristics is made and the results show that MMAS outperforms commercial heuristics.

Harrington et al. (2018), published one of the most important articles in the literature for this thesis. The research group formed a swarm that includes Coast Guard and UAVs. They consider the environmental factors in their model like currents, wind and weather conditions as well as complex interactions such as communication, detection and intercept. System detects the suspicious boats, rank them and decides which boat to infer. Results show that the overall success of the system is positively correlated with number of coast guards.

3. METHODOLOGY

This section consists of two subsections, where the first subsection presents flight statues of UAVs and their energy consumptions in these statuses. The second subsection presents our assumptions and LRP model.

3.1 Energy Consumption Models

There exist three flight statuses for UAVs, namely vertical take-off and landing, cruising (horizontal movement), and hovering (Thibotuwawa et al. 2018). Vertical take-off and landing statuses are observed when an UAV is launched from the main depot or a station, and when it returns to the main depot or arrives to a station for its battery to be swapped. Cruising status is observed between any two nodes in the graph, and is decomposed into three phases, namely, acceleration until the UAV reaches to a constant speed, horizontal movement at the constant speed, and deceleration when the UAV reaches to a neighborhood of the next node to be visited. Hovering status, however, is only observed over a target point for the UAV to take photos or videos of that point. Below, we give the total energy consumed by an UAV at each of these flight statuses.

Let $P_{c\,lim\,b}$ and P_{desc} be the powers absorbed by an UAV for taking off and landing, and $v_{c\,lim\,b}$ and v_{desc} be the speeds of the UAV for taking off and landing, respectively. These $v_{c\,lim\,b}$ and v_{desc} are assumed to be constant by Franco and Buttazzo (2016). Furthermore let Δh be the change in altitude. Assuming that each time the UAV is launched from altitude zero and it climbs up to an altitude h (i.e., $\Delta h = h$), the total energy consumed by the UAV is given by

$$E_{climb} = \int_0^{t_{climb}} P_{climb} dt = P_{climb} \frac{h}{v_{climb}} \tag{1}$$

where $t_{c\,lim\,b} = h/v_{c\,lim\,b}$ is the total time spent for climbing. Similar to (1), the total energy consumed while descending from an altitude h to the altitude zero is given by

$$E_{desc} = \int_0^{t_{desc}} P_{desc} dt = P_{desc} \frac{h}{v_{desc}} \tag{2}$$

where $t_{desc} = h/v_{desc}$ is the total time spent for descending.

Let P_{hover} be the power absorbed by an UAV while hovering and t_{hover} be the hovering time. This P_{hover} is defined by $P_{hover} = (\beta + \alpha h)$ in Pugliese et al. (2016), where β is the minimum power needed to hover at an altitude almost zero and α is the motor speed multiplier; both α and β depend on the weight and motor/propeller characteristics of the UAV. Now, the total energy consumed during hovering is given by

$$E_{hover} = \int_0^{t_{hover}} P_{hover} dt = (\beta + \alpha h) t_{hover} \tag{3}$$

Moreover, an UAV spends extra power while rotating Franco and Buttazzo (2016) as it is shown in Figure 3.1. Let P_{rotate} be the power absorbed during rotation, $\Delta\theta$ be the angle in radians covered by the rotation, and w_{rotate} be the rotational speed. Then, Franco and Buttazzo (2016) gives the energy consumed by rotation of the UAVs as

$$E_{rotate} = P_{rotate} \frac{\Delta\theta}{w_{rotate}} \tag{4}$$

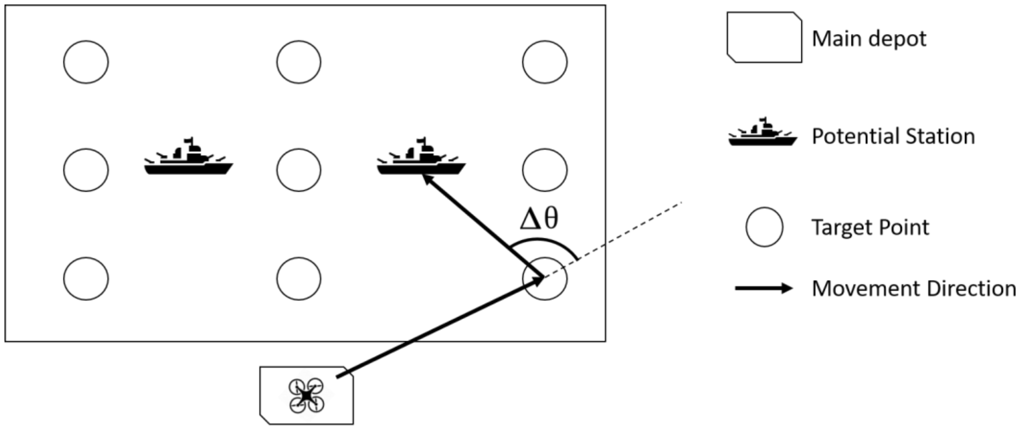

Figure 3.1. Rotational Movement of UAVs

Finally, let P_{acc}, P_{dec}, and P_{con} be the powers consumed by acceleration, deceleration and constant speed, respectively, and let t_{acc}, t_{dec}, and t_{con} be their respective durations. Then, the total energy consumed while moving horizontally is given in Franco and Buttazzo (2016) by

$$E_{climb} = \int_0^{t_{acc}} P_{acc} dt + \int_0^{t_{dec}} P_{dec} dt + \int_0^{t_{con}} P_{con} dt \\ = P_{acc}t_{acc} + P_{dec}t_{dec} + P_{con}t_{con} \quad (5)$$

To obtain t_{acc}, t_{dec}, and t_{con}, we make the same assumption as in Chowdurry et al. (2017) as follows. Let $d(i,j)$ be the Euclidean distance between any two nodes i and j in the graph; i.e.,

$d(i,j) = \sqrt{(abs(i) - abs\ (j))^2 + (ord(i) - ord(j))^2}$,

where $abs(.)$ and $ord(.)$ are the horizontal and vertical coordinates of a node, respectively. We assume that each time an UAV goes from node i to j, $a\%$ of the distance is spent for acceleration, and $b\%$ for deceleration. With this assumption, t_{acc}, t_{dec}, and t_{con} can be computed as in Chowdurry et al. (2017) by

$$t_{acc} = \sqrt{\frac{v_{con} m a\% d(i,j)}{P_{acc}}} \quad (6)$$

$$t_{dec} = \sqrt{\frac{v_{con} m b\% d(i,j)}{P_{dec}}} \tag{7}$$

$$t_{con} = \frac{(1 - a\% - b\%) d(i,j)}{v_{con}} \tag{8}$$

where v_{con} is the constant speed the UAV reaches after its phase of acceleration and m is the total payload of the UAV including its own weight. Note that all of the times t_{acc}, t_{dec} and t_{con} in (6), (7) and (8) respectively, depend on nodes i and j; yet, we do not show this dependence for notational simplicity. Now, E_{cruise} in Franco and Buttazzo (2016) can be computed by setting t_{acc}, t_{dec} and t_{con} in (6), (7) and (8) respectively, for any two nodes i and j.

3.2. LRP Formulation

This section presents first the assumptions and then the formulation. We assume the followings: (i) There is one main depot from which an UAV departs and to which that UAV returns after completing its mission; (ii) a potential station, if it is opened can only be used to swap the battery of an UAV and not for recharging (BSS) and battery costs are included in opening cost; (iii) the number of batteries stored at each open station is limited (i.e., capacitated facility); (iv) all sub-tours that do not start and end at the main depot have to be avoided; and (v) battery swap time is negligible. Before presenting the formulation, we have the remaining notation below.

$\boldsymbol{\tau}$	: Set of n target points
$\boldsymbol{C_k}$	: Set of m potential stations indexed by k
$\boldsymbol{\kappa_k}$	: Capacity of potential station k
$\boldsymbol{C'_k}$	: Set of dummy stations obtained by splitting potential station k into κ_k stations of capacity one
$\boldsymbol{C' = C'_1 \cup \ldots \cup C'_m}$	: Set of all dummy stations
$\boldsymbol{D = \{d_0, d_{n+1}\}}$	: Set of nodes representing the main depot (i.e., d_0 and d_{n+1} show the same site)

$\boldsymbol{v' = D \cup C' \cup \tau}$	: Set of nodes in an undirected graph $G = (v', \varepsilon')$ indexed by $i, j \in v'$
$\boldsymbol{\varepsilon'}$	: Set of edges *(i,j)* in $G = (v', \varepsilon')$
$\boldsymbol{v'_0}$	: Set of all nodes except d_0
$\boldsymbol{v'_{n+1}}$	: Set of all nodes except d_{n+1}
$\boldsymbol{S}$	: Fleet size
$\boldsymbol{f_k}$	: Fixed cost of opening potential station k
$\boldsymbol{c}$	: Per unit distance operating cost of an UAV
$\boldsymbol{T}$	: Total energy of a fully charged battery
$\boldsymbol{p}\%$	: Percentage of total consumable energy of a fully charged battery
$\boldsymbol{U = \sum_{k \in C} \kappa_k}$	: Total capacity of$G = (v', \varepsilon')$
$\boldsymbol{y_k}$	: 0-1 decision variable with y_k=1 if potential station k is open and y_k= 0 otherwise
$\boldsymbol{x_{ij}}$	: 0-1 decision variable with x_{ij}= 1 if edge *(i,j)* is traversed and x_{ij} = 0 otherwise
$\boldsymbol{z_i \geq 0}$	: Total remaining consumable energy in the battery after an UAV completes its Mission at node i (decision variable)
$\boldsymbol{t_i \geq 0}$	: Starting from the launch, the cumulative amount of energy consumed by an UAV up to and including node i (decision variable)

Now the problem is formulated as

$$Min \sum_{k \in C} f_k y_k + c \sum_{j \in v'_{n+1}} \sum_{i \in v'_0, j \neq i} d(i,j) x_{ij} \tag{9}$$

$$\sum_{j \in v'_0, j \neq i} x_{ij} \leq y_k \qquad \forall (i \in C'_k, k \in C) \tag{10}$$

$$\sum_{j \in v'_{n+1}} \sum_{i \in C'_k, i \neq j} x_{ji} \leq \kappa_k \qquad \forall k \in C \tag{11}$$

$$\sum_{i \in v'_{n+1}, i \neq j} x_{ij} = 1 \qquad \forall (j \in \tau) \qquad (12)$$

$$\sum_{j \in v'_0, j \neq i} x_{ij} - \sum_{j \in v'_{n+1}, j \neq i} x_{ji} = 0 \qquad \forall i \in \tau \cup C' \qquad (13)$$

$$\sum_{j \in v'_0} x_{d_0 j} \leq S \qquad (14)$$

$$z_j \leq p\%T - E_{c\,lim\,b} - (E_{cruise}(i,j) + E_{rotate} + E_{hover})x_{ij} \qquad \forall (i \in \{d_0\} \cup C', j \in \tau) \qquad (15)$$

$$z_j \leq z_i - (E_{cruise}(i,j) + E_{rotate} + E_{hover})x_{ij} + (p\%T - E_{c\,lim\,b})(1 - x_{ij}) \qquad \forall (i, j \in \tau, i \neq j) \qquad (16)$$

$$z_j \leq z_i - (E_{cruise}(i,j) + E_{rotate} + E_{desc})x_{ij} + (p\%T - E_{c\,lim\,b})(1 - x_{ij}) \qquad \forall (i \in \tau, j \in \{d_{n+1}\} \cup C') \qquad (17)$$

$$t_j \geq t_i + (E_{cruise}(i,j) + E_{rotate} + E_{hover})x_{ij} - Up\%T(1 - X_{ij}) \qquad \forall (i \in v'_{n+1}, j \in \tau\ i \neq j) \qquad (18)$$

$$t_j \geq t_i + (E_{cruise}(i,j) + E_{rotate} + E_{desc} + E_{c\,lim\,b})x_{ij} - Up\%T(1 - X_{ij}) \qquad \forall (i \in v'_{n+1}, j \in C' \cup \{d_{n+1}\}, i \neq j) \qquad (19)$$

$$T(1 - p\%) \leq z_i \leq p\%T(1 - x_{ij}) \qquad \forall i \in v' \qquad (20)$$

$$t_{d_0} \geq E_{c\,lim\,b} \qquad (21)$$

$$t_i \geq E_{c\,lim\,b} + E_{rotate} + E_{hover} \qquad \forall i \in \tau \qquad (22)$$

$$t_i \geq E_{c\,lim\,b} + E_{rotate} + E_{desc} \qquad \forall i \in C' \cup \{d_{n+1}\} \qquad (23)$$

$$t_i \leq Up\%T \qquad \forall i \in v' \qquad (24)$$

$$y_k \in \{0,1\}, x_{ij} \in \{0,1\} \qquad \forall (k \in C, (i,j) \in \varepsilon') \qquad (25)$$

where $\forall(.)$ means that the set of constraints holds for all indices within the parentheses. The objective function and constraints given above can be explained as follows. The objective function (9) is to minimize the total overall cost that includes opening costs of potential stations and operating costs of UAV which depends on the travelled distance. The first constraint (10) ensures the connectivity of potential station k if it is open. The constraint (11) limits the battery capacity for potential station k. The condition of VRP to visit each node only once is ensured by constraint (12). The constraint (13) is the set of flow balance constraint while the constraint (14) restricts the number of UAVs to be launched to the fleet size.

The remaining constraints are novel to the literature; therefore, they are detailed as follows. The constraints (15), (16) and (17) limit the remaining amounts of consumable energy depending on the types of nodes from which the UAV departs (node i) and to which the UAV arrives (node j). In the constraint (15), node i is the main depot or potential station and node j is a target point. In the constraint (16) both i and j are target nodes points while in the constraint (17), i denotes target points and j is the main depot or potential station. These constraints provide the remaining amounts of consumable energy if x_{ij}= 1. Otherwise, they provide a valid upper bound $p\%T - E_{c\,lim\,b}$ on the amounts of consumable energy. The constraint (20), also known as box constraints, controls the amount of consumable energy. In Franco and Buttazzo (2016), it is stated that from the fully charged battery, T, only 60%-70% can be consumed; therefore, we set $p\%$ = 70%.

Finally, the constraints (18) and (19) give, starting from their launches, the cumulative amounts of energy consumed by UAVs up to and including node i if they are active (i.e., x_{ij}= 1), and they give valid lower bounds on t_j otherwise. The constraint (18) is for a target point j, and the constraint (19) is for the main depot or potential station j. The remaining constraints provide lower and upper bounds on the cumulative amounts of energy consumed up to and including node i. In particular, the upper bound on the cumulative amount of energy spent by an UAV is given by $Up\%T$, where U is the total number of batteries stocked at all potential stations. The constraints (18) – (24) eliminate all sub-tours that do not start from and end at the main depot. The last constraint, namely constraint (25), ensures that y_k and x_{ij} take either 0 or 1, as values.

3.3 LPRTW Formulation

In this section the LRP formulation with Time Windows constraints are presented. In addition to the assumptions in Section 3.2, the followings are assumed: (vi) The UAVs are assumed to have a constants speed while cruising; (vii) some target points have specific time windows' to be hovered on. In this formulation, the following notations is added to the notation list of Section 3.2:

$\boldsymbol{q_i \geq 0}$	: Arrival time of UAV to node i (decision variable)
$\boldsymbol{l_i}$	: Allowed latest arrival time of UAVs to node i
$\boldsymbol{e_i}$	: Allowed earliest arrival time of UAVs to node i
$\boldsymbol{l_{d_{n+1}}}$	: Allowed latest arrival time of UAVs to main depot

The following constraints are combined with objective function (9) and constraints (10) – (17) and (25) from LRP in Section 3.2 formulation:

$$q_j \geq q_i + \left(t_h + \frac{d(i,j)}{v_{con}}\right) x_{ij} - l_{d_{n+1}}(1 - x_{ij}) \qquad \forall (i \in \tau, j \in v'_0\,) \qquad (26)$$

$$q_j \geq q_i + \left(\frac{h}{v\_climb} + \frac{d(i,j)}{v_{con}}\right) x_{ij} - l_{d_{n+1}}(1 - x_{ij}) \qquad \forall (i \in \{d_0\} \cup C', \; j \in v'_{n+1}\,) \qquad (27)$$

$$e_i \leq q_i \leq l_i \qquad \forall i \in v' \qquad (28)$$

Constraints (26) and (27) controls the arrival time of UAVs to target points, potential stations and depot. The time windows restrictions are enforced by constraint (28) to the model. These three constraints also eliminate the sub-tours.

4. COMPUTATIONAL ANALYSIS

This section provides numerical results for the two models introduced in Subsections 3.2 and 3.3. In Subsection 4.1, small size problems are solved to optimality for LRP model in Subsection 3.2, then sensitivity analysis is performed by changing some parameters. Then, the same analyses are performed for the problem introduced in subsection 3.3.

All solutions presented in Section 4 are obtained by Gurobi 8.1.1 Python API on a computer with Intel i5-8250 1.8 GHz CPU and 8 GB Ram.

4.1 Application of LRP to a Small Size Problem

We solved a small-size problem in an obstacle free environment for LRP model in 3.2. First, the base values of the parameters of the problem are determined. Then, some parameters are changed in order to form different scenarios. These scenarios are further solved and the results for each scenario are shown in Section 4.2.

In the problem we define nine target points, four potential stations with capacities and costs given in Table 4.1, and a single main depot, all located in a square of 1500m x 1500m. This area in the Mediterranean Sea is shown in Figure 4.1, and the arrows are declared as illegal migration paths by UNHCR.

Table 4.1: Potential Stations Specifications

Potential Station ID	Capacities (κ)	Costs (f)
1	2	2
2	3	3
3	3	5
4	2	5

Figure 4.1: Selected Region for Computational Analysis

We split potential station 1 into two stations of capacity one, potential station 2 into three stations of capacity one, potential station 3 into three stations of capacity one, and potential station 4 into two stations of capacity one which results in ten dummy stations of capacity one in $C' = \{3,4, \ldots, 12\}$. The sets of target points and the main depot are given by τ = {13, 14, …, 27} and D = {1,2} respectively.

The UAV parameters, based on Franco and Buttazzo (2016) and Pugliese et al. (2016) are given in the Table 4.2. to calculate the amount of energy consumption of the UAV in different flight statuses.

Table 4.2: Parameters of UAVs

Specification	Values
$P_{c\,lim\,b}$	320 Watt
P_{desc}	180 Watt
P_{rotate}	250 Watt
P_{acc}	270 Watt
P_{dec}	270 Watt
P_{con}	250 Watt
β	250 Watt
α	1
$v_{c\,lim\,b}$	10 m/s
v_{desc}	2.55 m/s
v_{con}	15 m/s
w_{rotate}	2.1 radians/s
$p\%$	70%

The chosen battery for the numeric study has a specification of 5200 mAh and 11.1 V, so T is calculated as 69264 Joules, and a and b are set to $a\%$=$b\%$=5%. The locations of all nodes are generated randomly according to a uniform distribution U (0, 1500) over two-dimensional and obstacle-free space.

Considering three UAVs, the optimal solution is presented in Figure 4.2. Only one UAV visits all target points, and potential station 1 (nodes 3 and 4) is opened. The optimal cost is found as 5,50E+19, and the optimal route is presented in Figure 4.2.

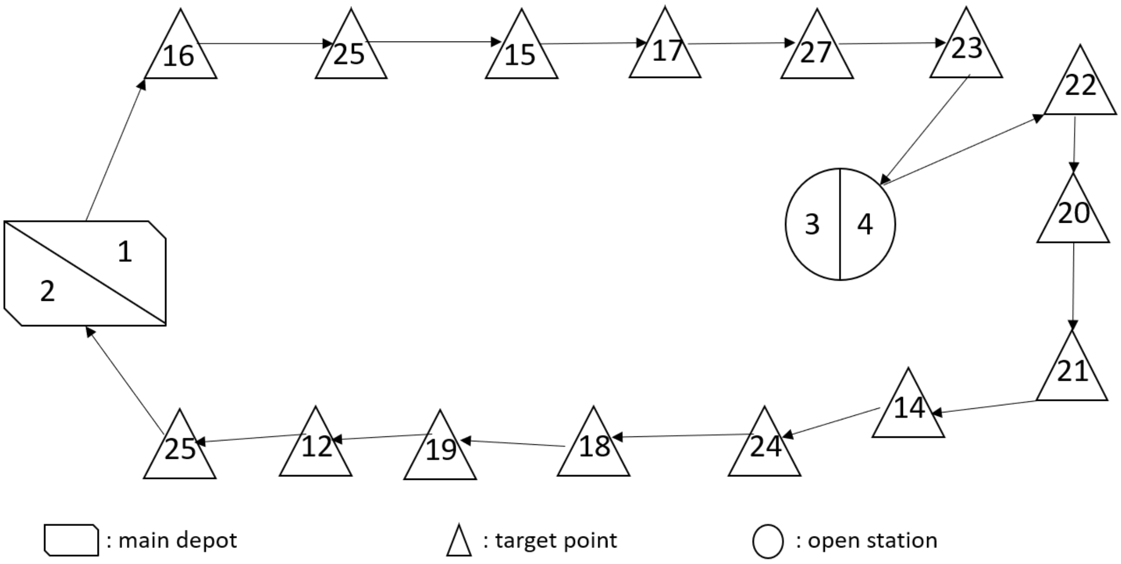

Figure 4.2: The optimal route of the formulation

4.2 Sensitivity Analysis of LRP

In this subsection some parameters of the problem are altered in order to examine the sensitivity of the proposed LRP model. Base case scenario is given in Table 4.2. Some specifications of UAVs are different from Section 4.1 which are h and p% and used as 100m and 75% respectively

4.2.1 Sensitivity to Range of Region

The range of the region that main depot, potential stations and target points are located is altered and the results are analyzed in this subsection. The observed area is enlarged by increasing the range of the region. Since the distance has a direct effect on the objective function, it is expected to lead an increase in the value of optimum solution. The model is applied to 1.5 km^2, 3 km^2, 7.5 km^2 and 10 km^2 without any time limitation on the solution time of the model. The locations of nodes are distributed uniformly and the results for objective function and run times are presented in the Table 4.3.

Table 4.3: Optimum Results for Different Ranges

Range of Region	Run Time (secs)	Optimum Solution
1.5km^2	40.98	5,46E+19
3km^2	49.66	1,09E+20
7.5km^2	52.75	2,76E+20
10 km^2	106	4,46E+20

It can be seen in Table 4.3 that both the optimal solution and the run times increase with the range.

4.2.2 Sensitivity to the Number of Target Points

With 5 minutes time limitation, the sensitivity of the proposed model to the number of target points is analyzed in this subsection in 3 km^2 region. Since all target points must be visited by an UAV, the increase in the number of target points is expected to lead an increase in the value of the optimum solution. The number target points are increased from 15 to 21 and the results for objective function and run times are shown in Table 4.4.

Table 4.4: Optimum Results for Different Number of Nodes

Number of Target Points	Optimum Solution	Run Time (secs)	C_1	C_2	C_3	C_4
15	1,094E+19	49,66	0	0	0	1
16	1,174E+19	8,02	1	0	0	0
17	1,117E+19	1,27	0	0	1	0
18	1,124E+19	7,59	0	0	0	1
19	1,125E+19	12,93	0	0	0	1
20	1,180E+19	159,79	0	0	0	1
21	-	Time Limit	-	-	-	-

As it can be seen from Table 4.4, the increase in number of target points resulted with an increase in the value of optimum solution. However, there is a decrease in the value of optimum solution while the number of target points is increased from 16 to 17. In addition, the increasing rate fluctuates. These inconsistencies occurred because the locations for each number of target points are generated randomly.

The same inconsistency is detected for the run times because of the random generation process. And, when 21 target points deployed in the model, the solution cannot be gathered in 5 minutes.

4.2.3 Sensitivity to Flying Altitude

In this subsection, the sensitivity of the proposed model to flying altitude of UAVs is examined. The tradeoff in the context of our problem, for flying altitude, is while UAV climbs higher altitudes the probability of UAV to be detected decreases, however the energy consumption increases accordingly.

Flying altitude effects energy consumption in both take-off and landing since it is the distance to be travelled in both actions. These two actions require substantial amount of power each time when an UAV visits a potential station or main depot. So, the increase in the flying altitude is expected to lead an increase in the value of optimum solution. The model is applied in a region of 3 km^2, and the results are shown in Table 4.5.

Table 4.5: Results of Flying Altitude is 3 km^2

Altitude	Optimum Solution	Solution Time (secs)	C_1	C_2	C_3	C_4
110	1,10E+20	54,94	1	1	0	1
120	1,10E+20	65,66	1	1	0	1
130	1,10E+20	29,19	1	1	0	1
140	1,10E+20	46,45	1	0	0	0
170	1,10E+20	19,56	1	0	0	1
200	1,18E+20	254,43	1	0	0	1
250	-	Time Limit	-	-	-	-

When the region is 3 km^2, the change in the optimum solution is small, even negligible between 100m to 170 m. So, the same study is applied to 7.5 km^2 region in order to show the effect of altitude clearly. The results are shown in Table 4.6.

Table 4.6: Results of Flying Altitude in 7.5 km2

Altitude	Optimum Solution	Solution Time (secs)	C_1	C_2	C_3	C_4
110	2,78E+20	27,82	1	1	0	1
120	2,98E+20	181,47	1	1	0	1
130	3,16E+20	298,05	1	1	0	1
140	-	Time Limit	-	-	-	-

As it can be seen from Table 4.6, when the altitude increases, the optimum solution and the run time increase concurrently. It can be concluded that altitude is not effective on the value of optimum solution unless it causes to open or revisit a potential station, because altitude is not considered in objective function. It only stresses the energy consumption constraints. So, in 7.5 km^2 region, higher altitudes cause revisits to opened potential station and changes in optimum value becomes visible. However, when the altitude is 140m, run time limitation is reached and optimum solution couldn't be found.

4.2.4 Sensitivity to Hovering Time

In this subsection, with different hovering time, the sensitivity of the proposed model is examined. Hovering time is also referred as service time of the node in literature. In our context, it is the time that an UAV spends over a target point to monitor. The tradeoff for this parameter is with higher hovering times, the image quality increases, however the energy consumption increases as well. So, it is expected that the optimum solution to increases with the hovering time. The results of the analysis in 7.5 km^2 are shown in Table 4.7.

Table 4.7: Results of Hovering Time

Hovering Time (secs)	Optimum Solution	Solution Time (secs)	C_1	C_2	C_3	C_4
5	3,34E+20	515,86	1	1	0	1
10	3,49E+20	100,13	1	1	1	1
15	4,18E+20	178,25	1	1	1	1
20	5,24E+20	228,92	1	1	1	1
25	infeasible	-	-	-	-	-

As it can be seen from Table 4.7, higher hovering times result in higher optimum solutions by opening a new station or revisiting an opened station several times. And the problem becomes infeasible in 25 seconds. So, we can say that hovering time is one of the most important parameters for the feasibility of the problem considering the limited battery capacity.

In Table 4.7 the solution time of t_h = 5 secs, is higher than the other hovering times. This can be explained as follows; when the hovering time is small, the amount of remaining energy of UAVs increases. This leads to more options for UAVs to visit next; i.e. if the remaining energy of UAVs is low, then they have to go to an open station to swap batteries. However, with a higher level of energy UAVs can visit target points or potential stations.

4.2.5 Sensitivity to Cost of Opening a Potential Station

In this subsection, opening a potential station cost is altered in order to see the sensitivity of the model. In the current problem the effect of this cost is small when it is compared with the distances. In order to make opening cost more effective, we first multiply the costs with 100 and alter it accordingly in 7.5 km^2 region. The results are shown in Table 4.8.

Table 4.8: Results of Cost Changes

Costs for C_1, C_2, C_3 and C_4	Optimum Solution	Number of Deployed UAVs	Opened Sations
2, 3, 5, 5	2,76E+20	1	C_1 and C_4
200, 300, 500, 500	3,41E+20	1	C_1 and C_4
1000, 200, 200, 1000	2,89E+20	2	C_1
10000, 200, 200, 1000	3,25E+20	1	C_3 and C_4

With bigger fixed costs, optimum solution increases drastically; however, the optimal routes are not changed.

Therefore, we directly manipulated the opening costs of C_1 and C_4 with multiplying them by 2 in order to see a difference in the route, since they were opened in the previous case.

With these parameters, the value of optimum solution is decreased, number of deployed UAVs increased, and only C_1 is opened. Opening a new station is more expensive than routing a new UAV in this case. The decrease in the value of optimum solution can be explained as follows; in the previous case with small opening costs, an UAV visits C_1 twice and C_4 once; however, with bigger costs, it only visits C_1 once. So, the decrease in the value of the optimum solution is a result of the decrease in travelled distance.

In the last scenario, the cost of opening C_1 is multiplied by 10 since it is the only station opened in the previous scenario. The optimum solution increases. This time, opening C_3 and C_4 becomes advantageous rather than deploying a new UAV.

As conclusion, we have seen that manipulating costs has direct effect on the solution in every aspect such as optimum route, opened stations, number of deployed UAVs and optimum solution.

4.3 Application of LRPTW to Small Size Problem

As a numerical study for LRPTW model, the predefined parameters in Subsection 4.1 are used as base specifications in order to compare models in small scale solutions. Then, with changing the parameters the sensitivity analysis is performed on the model. In the study, first the critical targets determined and their time windows are allocated. Henceforth, the maximum mission duration is set to 10 minutes. The critical target points due to their locations on the route of illegal migration are target point 15, 19, 22 and 24. The time limitations for these critical target points are presented in Table 4.9.

Table 4.9: Time Windows of Critical Target Points (in seconds)

Target	Lower Bound	Upper Bound
15	120	120
19	100	300
22	100	600
24	120	350

Target 15 has a hard time windows constraint which ensures that an UAV starts hovering onto target at 120 secs after the start of its mission. Time windows for targets 19 and 24, enforce UAVs not to start hovering onto these targets before 100 and 120 secs, and after 300 and 350 secs, respectively. Lastly, target 22 has the limitation of earliest starting to hover time which is 100 secs.

The optimal route for UAVs to follow is given in Figure 4.3.

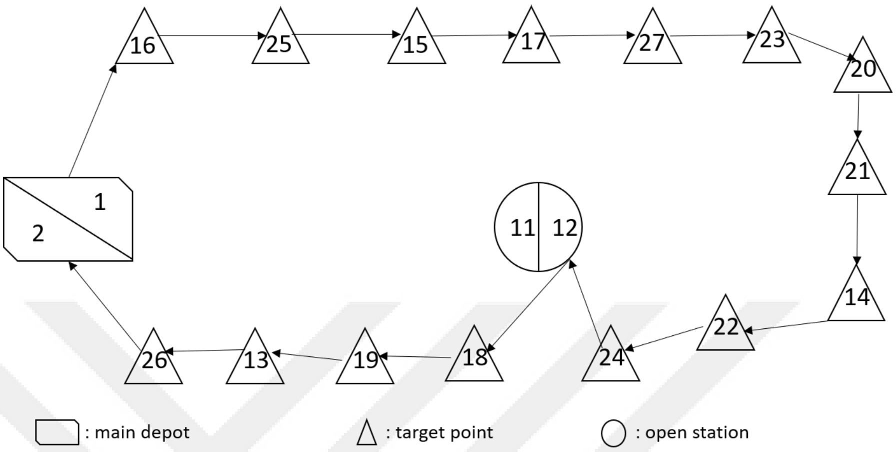

Figure 4.3: Optimal Route of LRPTW

As it can be seen from Figure 4.3, only one UAV is deployed for mission same with the LRP formulation however, potential station 4 (nodes 11 and 12) is opened instead of 1 and little changes occurred in the order of visited targets. The objective function is found as 5.62E+19 which is higher than LRP formulation. This situation can be explained as follows; since UAVs have to satisfy more constraints, this enforces UAVs to take longer trips and opening potential station 4 which has higher cost then 1.

4.4 Sensitivity Analysis of LRPTW

In this subsection the sensitivity of LRPTW model to changes in parameters is presented. The base case scenario parameters used for sensitivity analysis are as given in Subsection 4.2 and run time is limited to 10 minutes throughout Subsection 4.4 unless otherwise stated.

4.4.1 Effect of Time Windows

In this subsection the effect of time windows is examined with the comparison of cases with time windows for target points and maximum mission duration, only maximum mission duration and no time windows at all. For each case, the rest of the parameters remain the same. It is expected that the addition of time windows increases the value of optimum solution. Three cases analyzed in 3 km^2 region, with 600 secs maximum mission duration (if existed) and the results are shown in Table 4.10.

Table 4.10: Results of Time Windows Study

Time Windows for Target Points	Optimum Solution	Solution Time (secs)	Number of Deployed UAVs	Number of Opened Stations
Yes	1,31E+20	149,22	2	0
No TW for target points but with maximum mission duration	1,22E+20	648,6	2	0
No TW at all	1,09E+20	44,96	1	1

In Table 4.10, the increase in optimum solution is clear with the addition of time windows for maximum mission duration and for target points. With the addition of maximum mission duration, the number of deployed UAVs is increased from 1 to 2 in order to satisfy the limitation but it doesn't induce opening a new station. Since the number of deployed UAVs is not considered as cost in our model this increase can be explained as a result of excessive distance traveled in the existence of only maximum mission duration. In the no time windows case, a potential station is opened. However, this situation doesn't affect the optimum solution as much as traveled distance. So, this leads us to conclude that costs of potential stations are not as effective as cost of travel.

The increase in the value of optimum solutions between the cases with only maximum mission duration and with time windows for target points and maximum mission duration is clear to see. With the addition of time windows for target points, which means bringing new limitations, increases the value of optimum solution. Since UAVs have to reach some specific targets within some specific time intervals, they travel more than the previous case but opening a new station is not required in both cases.

4.4.2 Sensitivity to Maximum Mission Duration

Maximum mission duration is the time that is allocated for UAVs to end their route and return to the main depot after visiting every target point. In this subsection maximum mission duration is altered from 600 secs (10 mins) to 360 secs (6mins) in 3 km^2 region with some target points to have specific time windows. The results are presented in Table 4.11.

Table 4.11: Results of Changes in Maximum Mission Duration

Maximum Mission Duration (secs)	Optimum Solution	Solution Time (secs)	Number of Deployed UAVs
600	1,31E+20	144,06	2
540	1,31E+20	172,73	2
480	1,31E+20	200,03	2
420	1,59E+20	2296,03	3
360	infeasible	-	-

As it can be seen from Table 4.11, when the maximum mission duration is between 600 secs and 480 secs, the value of optimum solution and number of deployed UAVs remain the same. However, solution time increases while maximum mission duration decreases. Number of deployed UAVs is 3 when maximum mission duration is 420 and the run time increases dramatically to 2296.03 secs. It is seen that, in LRPTW model more than one UAV is deployed, which is different than the solution of the LRP model. So, addition of time windows and narrowing them increase the number of the deployed UAVs, run times and the optimum solutions. The number of opened potential stations is not shown since none is opened.

4.4.3 Sensitivity to the Number of Target Points

In this subsection, the sensitivity of LRPTW model to the number of target points is examined with alteration from 15 target points to 19 in 3km^2. The results are shown in Table 4.12.

Table 4.12: Results of Changes in Number of Target Points

Number of Targets	Optimum Solution	Solution Time (secs)	Number of Deployed UAVs
15	1,31E+20	144,06	2
16	1,25E+20	1,29	2
17	1,20E+20	4,99	2
18	1,29E+20	1,65	2
19	infeasible	-	-

Even though the increase in the value of optimum solution is expected with the increase in the number target points, this is not observed in the solutions except between 17 target points and 18 target points. This and run time volatility is again the result of random number generation process from scratch for each number of targets parameter. The problem is infeasible when number of target points is 19 or higher with time windows constraints. The number of deployed UAVs is again more than LRP model, and 2 throughout the process.

4.4.4 Sensitivity to Flying Altitude

In this subsection the sensitivity of LRPTW model to flying altitude of UAVs is examined. In the study, the flying altitude is altered from 100m to 250m. The tradeoff is the same with the LRP model. That is, higher altitude decreases the probability of detectability while increasing the energy consumption. So, it is expected for the value of optimum solution to increase with respect to flying altitude. The results are shown in Table 4.13 with 10 minutes time limitation.

Table 4.13: Results of Changes in Flying Altitude

Flying Altitude (m)	Optimum Solution	Solution Time (secs)	Number of Deployed UAVs	Number of Opened Stations
100	1,31E+20	144,06	2	0
110	1,31E+20	86,76	2	0
130	1,31E+20	91,14	2	0
200	1,31E+20	148,9	2	0
250	1,55E+20	239,36	2	2

Since the flying altitude is not included in the objective function, it only effects optimum solution when it causes a revisit to opened station or a new station to open. The value of optimum solution is not changed between 100m and 200m of altitude. Therefore, it means that the increase in energy usage while altitude is in between 100 and 200 m doesn't require to open a station. However, it is seen that in 250 m, number of opened stations is 2 which is the reason of the increase in the value of optimum solution.

4.4.5 Sensitivity to Hovering Time

In this subsection the sensitivity of LRPTW model to hovering time is examined. The tradeoff in the context of this study, as it is mentioned in Subsection 4.2.4, is higher hovering time increases the image quality while leading higher energy consumption as well. So, the expectation is to get higher values of optimum solution in higher hovering times. The runs are taken with 10 mins time limitation and results are shown in Table 4.14.

Table 4.14: Results of Changes in Hovering time

Hovering Time (secs)	Optimum Solution	Solution Time (secs)	Number of Deployed UAVs	Number of Opened Stations
2	1,31E+20	149,22	2	0
5	1,31E+20	191,27	2	0
10	1,39E+20	35,6	2	2
15	1,76E+20	402,36	2	2
20	-	Time Limit	-	-

As it can be seen from Table 4.14, the optimum solution increases with the increase in hovering time except the change from 2 secs to 5 secs. There is no change in the optimum value between 2 to 5 secs. This is because the number of opened stations is not changed in the optimum solution. When we compare the change occurred in the value of optimum solution with other parameter changes, hovering time has bigger effect on the optimum value. Therefore, hovering time can be named as one of the most important factors in LRPTW model.

5. CONCLUSION

In this thesis, this refugee problem is taken into consideration with the technology of UAV. We propose a surveillance strategy in Aegean Sea, which is one of the crucial routes, to deploy UAVs in order to detect refugee boats before they sunk. Therefore, a routing problem of UAVs arises. The problem is considered as a Location Routing Problem where the simultaneous decisions of UAV routes and opening intermediate charging facilities are made. In the disaster management literature, this study is placed in the mitigation phase where the prevention actions or effect reducing actions are taken.

Two models are proposed in this context. The first one is LRP formulation which UAV specific energy models are embedded into formulation and novel subtour elimination constraints are presented. The second one is LRP formulation with Time Windows, which keeps the UAV specific energy models in the formulation, more realistic and case based, and subtours are eliminated by time windows constraints without having any extra constraints.

Then, computational study is performed on two models with changing parameters and evaluating the effects of changes on the value of optimum solution. First, the base parameters for UAVs and problem are determined and small size studies are performed in both models. The changes are first applied on LRP formulation to parameters of (i) range of region that mission is due on, (ii) number of target points to be visited, (iii) flying altitude of UAVs, (iv) hovering time of UAVs on target points and (v) cost of opening potential stations. Then the changes are applied on LRPTW formulation with altering (i) the status of time windows, (ii) maximum mission duration, (iii) number of target points to be visited, (iv) flying altitude of UAVs and (v) hovering time of UAVs on target points.

In the computational study of LRP, it is seen that when we enlarged the area for UAVs to survey, the cost which is the minimizing objective function and run times increase accordingly. The same trend is observed in objective function while increasing the number of target points to be surveyed. It is because, with the increase of target points the distance travelled increases. However, since we locate the nodes on the graph with random distribution for each number of target points, there are some volatility of the amount of both run times and the value of optimum solutions.

For flying altitude, two studies are conducted which are the studies on 3 km^2 and 7.5 km^2 regions. In 3 km2 region, the increase in altitude did not cause a big increase in objective function. It is because, the altitude has no direct effect on the objective function it only has an effect if it leads an opening to a new station or a revisit to an opened station. So, in order to see the effect the same study conducted to 7.5 km2 and the increase in the value of optimum solution became visible.

On the other hand, hovering time is one of the most effective parameters in the study. The effect of increase in hovering time is visible in the value of optimum solution directly. Even thought, it is not included in objective function, it makes UAVs to visit a charging station more frequent in higher hovering times.

In the study, the cost sensitivity is crucial since we can directly manipulate the objective function. It is seen that, with the changes in cost of opening potential stations not only the value of optimum solution fluctuates, also the whole route and most importantly number of deployed UAVs changed for the first time throughout the LRP computational study.

After the solution of small size problem for LRPTW, the effect of adding time windows is studied with changing time windows status. The examined three cases are as follows: (i) no time windows at all, (ii) only maximum mission duration and (iii) both time windows for target points and maximum mission duration. The value of the optimum solution increased along cases (i)-(iii). The number of UAVs is increased from 1 to 2, with the addition of time windows. And also, deploying new UAV is cheaper than opening a new station in time windows existence.

For maximum mission duration, while the duration shortened up to a significant level, the value of objective function and run time increases. In the study of number of target points, the same situation with the LRP arises which is the result of random distribution of locations of nodes. Run times and the value of optimum solution fluctuates.

On the other hand, flying altitude and hovering time showed the same effect in LRPTW as they shown in LRP. They have an impact on objective function with causing opening a new station or a revisit to opened station.

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PUBLICATIONS

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