MARMARA UNIVERSITY

INSTITUTE FOR GRADUATE STUDIES
IN PURE AND APPLIED SCIENCES

RISK-BASED DRONE ROUTING USING A HYBRID SWARM INTELLIGENCE ALGORITHM

EZGİ KAYIŞ

MASTER THESIS

Department of Industrial Engineering

Thesis Supervisor
Asst. Prof. Dr. Merve ER

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In this thesis, the popular and frequently studied drone delivery and drone routing problem has been studied and the performances of swarm intelligence algorithms on the problem have been compared by focusing on the multi-package delivery with single drone concept, which is a new perspective. I hope that this study can provide useful information to the field of multi-package delivery with a single drone, which does not yet have a real-life application, and contribute to both national and international package delivery applications. I am grateful to my valuable advisor, Asst. Prof. Dr. Merve ER, for her endless support and guidance throughout the thesis process, as well as her outstanding patience. Her guidance and valuable feedback throughout my thesis have a great impact on my academic development. Completion of the thesis would not have been possible without her knowledge and experience. I would like to express my gratitude to my beloved family who supported me throughout my academic life; I always felt strong thanks to their support, motivation and love. Their patience and understanding throughout my educational journey played a huge role in achieving my goals.

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ABSTRACT

RISK-BASED DRONE ROUTING USING A HYBRID SWARM INTELLIGENCE ALGORITHM

With technological developments in recent years, the use of drones has increased. Today, there are various drones operating in different fields, and their use continues to become widespread in many areas such as military operations, surveillance and reconnaissance, disaster management, environmental modeling or logistics. These vehicles may encounter some threats during their use, such as restriction area, extreme weather conditions (hot weather, wind, etc.), attacks or geographical conditions. Determining the optimum route under these threats is fundamental. Swarm intelligence algorithms, in particular, offer effective solutions to solve such complex optimization problems. Swarm Intelligence Algorithms are inspired by the behaviors of living creatures in nature and integrate these behaviors into artificial systems.

In this thesis, the drone routing problem, which is increasingly used in the transportation and logistics sector, is discussed. Today, it is known that many developed companies are working on drone delivery applications in order to improve their deliveries and optimize their processes. In this study, a risk-based route optimization model is developed for a single drone with high future applicability and ability to make multiple deliveries. In addition to the distance minimization objective of the conventional routing problems, it is aimed to optimize the route to include minimum risk, considering the risk factor that the drone can be exposed to during its journey. In solving the problem, the 2-Opt Harmony Based Artificial Bee Colony (HABC-2O) approach is employed by combining the Harmony Search Algorithm (HS) and the Artificial Bee Colony Algorithm (ABC). HABC-2O has been compared to classical ABC and Ant Colony Algorithm (ACO).

Keywords; Artificial Bee Colony Algorithm, Ant Colony Algorithm, Drone Routing, Unmanned Aerial Vehicles, Swarm Intelligence, Harmony Search Algorithm

ÖZET

HİBRİT SÜRÜ ZEKASI ALGORİTMASI KULLANARAK RİSK TEMELLİ DRONE ROTALAMA

Son yıllardaki teknolojik gelişmelerle drone kullanımı artmıştır. Günümüzde farklı alanlarda görev yapan çeşitli drone'lar bulunmakta ve askeri harekat, gözetleme ve keşif, afet yönetimi, çevre modelleme veya lojistik gibi birçok alanda kullanımı yaygınlaşmaya devam etmektedir. Bu araçlar kullanımı boyunca kısıtlama alanı, aşırı hava koşulları (sıcak hava, rüzgar vb.), saldırılar veya coğrafi koşullar gibi bazı tehditlerle karşılaşabilmektedir. Bu tehditler altında optimum rotanın belirlenmesi oldukça önemlidir. Özellikle sürü zekası algoritmaları, bu tür karmaşık optimizasyon problemlerini çözmek için etkili çözümler sunar. Sürü Zekası Algoritmaları, doğadaki canlıların davranışlarından ilham alır ve bu davranışları yapay sistemlere entegre eder.

Bu tezde teslimat ve lojistik sektöründeki kullanımı gittikçe artmakta olan drone rotalama problemi ele alınmıştır. Günümüzde pek çok gelişmiş firmanın teslimatlarını iyileştirebilmek ve süreçlerini optimize edebilmek için drone ile teslimat uygulamaları üzerine çalıştığı bilinmektedir. Bu çalışmada, gelecekte uygulanabilirliği yüksek, birden fazla teslimat yapabilen tek bir drone için risk-tabanlı bir rota optimizasyonu modeli geliştirilmiştir. Alışılagelmiş rota problemlerinin mesafe minimizasyonu amacına ek olarak, drone'un seyahati sırasında maruz kalacağı risk faktörünü de hesaba katarak rotanın minimum risk içerecek şekilde optimize edilmesi amaçlanmıştır. Problemin çözümünde, Harmony Search Algoritması (HS) ve Yapay Arı Kolonisi Algoritması (ABC) birleştirilerek, 2-Opt'lu Armoni Tabanlı Yapay Arı Kolonisi (HABC-2O) yaklaşımı uygulanmıştır. HABC-2O, klasik ABC ve Karınca Kolonisi Algoritması (ACO) ile karşılaştırılmıştır.

Anahtar Kelimeler; Yapay Arı Kolonisi Algoritması, Karınca Kolonisi Algoritması, Drone Rotalama, İnsansız Hava Araçları, Sürü Zekası, Harmony Arama Algoritması

SYMBOLS

AC : Abandonment counter

AL : Abandonment limit

D : Dimension of the problem

d : Distance between nodes

FN : Number of initial food source

u : Upper bound for variable

l : Lower bound of variable

n : Total number of nodes

r : Level of risk exposure

p : Probability values

SN : Number of bees

ABBREVIATIONS

ABCUR : Artificial Bee Colony-Based UAV Routing
ACO : Ant Colony Optimization
AHP : Analytical Network Processes
ALNS : Adaptive Large Neighbourhood Systems
AUAV : Vehicle Routing Problem with Drones
BCA : Bee Colony Algorithm
BCP : Branch and Cut Price
BFA : Bacterial Foraging Algorithm
FA : Firefly Algorithm
GA : Genetic Algorithm
HS : Harmony Search
HSMS : Harmony Search Memory Size
ILP : Integer Linear Programming
PAR : Pitch Adjustment Rate
PSO : Particle Swarm Optimization
RPAS : Remotely Piloted Aircraft Systems
SI : Swarm Intelligence
TSP : Travelling Salesman Problem
UAS : Unmanned Aerial Systems
UAV : Unmanned Aerial Vehicles
UAVRP : Unmanned Aerial Vehicles Routing Problems
UCAV : Unmanned Combat Aerial Vehicles
VRP : Vehicle Routing Problem
VRPD : Vehicle Routing Problem with Drone

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1. INTRODUCTION

The rapidly advancing technology enables the current era to develop continuously and to open new breakthrough paths for people. With technology, not only people can strengthen their own virtues, but also allow systems to exist that can provide human virtues without the need for human intervention. Advanced technologies such as robots and autonomous systems provide a way to reduce dependency on humans and thus avoid dangerous situations that challenge human nature. One of the most important representatives of these developments is unmanned systems, which is a pioneering approach in human-dependent sectors such as the defence, transportation, collection, tracking and distribution sector. One of the most popular unmanned systems covering land, sea or air systems is undoubtedly the unmanned aerial vehicles in the aviation sector. According to the Global Air Traffic Management Operational Concept, UAVs are flying vehicles developed with remote control or autonomous technology that do not have a pilot or a driver (International Civil Aviation Organization, 2005). These vehicles can be positioned/equipped with equipment and tools suitable for the use of purpose (Kahveci & Can, 2017).

Nowadays, there are various UAVs that perform in different areas and their use continues to be widespread in many fields such as military operations, surveillance and reconnaissance studies, disaster management, environment modelling, camera shooting or lojistics. With the changing and increasing needs over time and the advancement of technology, the use of unmanned aerial vehicles has become widespread, and the routing of these aircrafts became significant consequently. UAV routing is similar to the Vehicle Routing Problem (VRP). The VRP optimizes the routing problems of vehicles which delivers good from a depot to the customers. Similarly, in drone routing, customers are accepted as targets and warehouse point is the starting and landing point for drone at the end of the route (Faied et al. 2010). Chowdhury et al. (2021) states that: "*Drone routing can be considered as a special case of VRP where various complexities are introduced within traditional VRPs based on drones' physical and routing limitations.*". Routing of UAVs is more complex than VRP, as it includes many additional factors such as flight or system dynamics of UAVs. Some of these factors may be listed as battery life, focus on 3D environment rather than 2D, changing weather and wind conditions, or avoidance from moving and stationary objects.

The routes to be followed by the UAVs and the planning of the tasks can be changed according to the events that it is encountered; therefore, route planning have become more important for the UAV systems. These vehicles may be exposed to various threats such as restriction area, extreme weather conditions (hot weather, wind, humidity, etc.), attacks to drones, geographical conditions or exposure to a signal interrupter. Therefore, identification of the optimum route under these threats is a very complex and difficult problem. Additionally, there are lots of variants of this problem that considers different factors such as flight dynamics, fixed flight time, problem space dimension, fuel consumption, environmental conditions, etc.

The main purpose of this thesis is to solve this hard and complex optimization problem, Routing of UAV, that includes some threats and external factors. The purpose of the UAV path planning and routing problem is to ensure that the UAV route is established in the most effective and efficient way. Hence, UAVs are able to complete the targeted task by using their battery life and limited fuel in the most efficient way in the face of obstacles and external effects. The solution of the drone routing problem can be based on a swarm intelligence algorithm. Swarm Intelligence is the discipline that deals with natural and artificial systems consisting of many individuals that coordinate their activities using decentralized control and self-organization (Cui & Gao, 2012). The trend towards Swarm Intelligence Algorithms is increasing in many complex engineering fields such as autonomous systems. There are various techniques in Swarm Intelligence area such as Ant Colony Optimization (Chandra Mohan & Baskaran, 2012), Particle Swarm Optimization (Gad, 2022), Artificial Bee Colony (Karaboğa, 2010), Bacterial Foraging Algorithm (Guo et al., 2021), etc. Swarm Intelligence provides many advantages to the problem-solving stage. For example, it is flexible, and it can offer different solutions according to changes. In addition, it provides rapid adaptation to new situations and conditions. It allows to create quick responses to changes. However, not every swarm intelligence algorithm is suitable for every system or situation. Therefore, the algorithm should be selected by considering its usefulness and potential for air operations. Swarm intelligence algorithms can provide great convenience in determining the artificial intelligence strategy of the unmanned aerial vehicles. The trend towards Swarm Intelligence Algorithms is increasing in many complex engineering fields. Nowadays, the work of many countries and companies have started to focus on minimizing the need for human in the use of UAVs. The use of UAV has begun to attract attention in many areas and has offered advantages as it reduces the need for humans. Especially drone delivery efforts have recently gained momentum and have begun to be implemented in real life.

In order to contribute to this growing area, this thesis proposes a risk-based UAV routing model based on swarm intelligence. In addition to the distance minimization objective of traditional models, environmental factors are also considered as a risk factor in the model. The problem focuses on the delivery of multiple packages by a single drone under risk. 2-Opt Harmony Based Artificial Bee Colony (HABC-2O) approach is employed by combining the Harmony Search Algorithm (HS) and the Artificial Bee Colony Algorithm (ABC). HABC-2O has been compared to classical ABC and Ant Colony Algorithm (ACO).

The remainder of the thesis is structured as follows. Chapter 2 provides a background for UAVs, UAV routing problem, and the use of Swarm Intelligence Algorithms to solve UAV routing problems. Chapter 3 explains the methodology used in the thesis. Chapter 4 presents the application and Chapter 5 gives the results and provides a discussion. Finally, Chapter 6 concludes the thesis.

2. LITERATURE REVIEW

This section provides a background on UAVs, UAV routing problem, and the use of Swarm Intelligence algorithms in this area.

2.1. Unmanned Aerial Vehicles (UAVS)

Unmanned Aerial Vehicle is a type of aircraft that may do its task remotely and/or autonomously. According to the definition in the NATO UAV document; Unmanned Aerial Vehicles are vehicles that support the desired aerodynamic flight forces without a pilot and can carry lethal or non-lethal payloads outside the missile route with remote control or automatic/autonomous flight (Altenburg, 2002). The definition of UAV used in official publications in Turkey is emphasizes that UAV is a fixed or stationary aircraft on the ground that does not contain a pilot. It is a motorized aircraft that is commanded by radio frequency waves from a mobile control station and forms a platform for the payload (camera, radar, weapon, etc.) mounted on it. The term more appropriate for the use of today's UAVs is not "Unmanned Aerial Vehicle" but "Aircraft Without a Pilot"; on account of the fact that the pilot on the ground can intervene in the flight, change the flight route, or cancel the mission completely at any time during the flight with remote control (Başak & Gülen, 2008). Unmanned Aerial Vehicles are sometimes referred to as drones in the literature, and the nomenclature has the same meaning, except for a few technical details. The word "drone" is used to describe both air and sea vehicles that can move automatically and have no driver; UAV, on the other hand, is used to refer to aircraft that are motorized, capable of unmanned flight and can be controlled remotely. With its extended terminology, it can also be used as Unmanned Aircraft Systems (Federal Aviation Administration, 2016). However, the word drone has become a word used more frequently to refer UAV.

The first officially accepted use of UAV in history is the air attack made by 200 flying balloons without a driver, loaded with time-warped bombs, sent to Venice by the Austrians in 1849. Considering flying unmanned balloons, it is possible to date military use even further back than this event; In 1793, unmanned balloons were used for reconnaissance purposes during the civil wars in the USA. In accordance with the definition of drone we know, the oldest examples are Elmer Sperrey flying a plane with the help of a flight controller (Uçar &İşleyen, 2019). Although the existence of unmanned aircraft in the military dates back to World War I, their use was only seen during World War II. It was used especially in military operations in important historical wars such as the Vietnam War and Iraq Wars, and its military use has increased since then.

Owing to the successful use in the military field, interest in Unmanned Aerial Vehicles has increased and it has pioneered the use of these vehicles in civilian life. It has had many different uses such as land exploration, observation, lojisticts, search and rescue. There is also considerable use in archaeological discoveries, city modelling and agricultural practices. For example, Xing et. al. (2024) highlighted the significance of UAVs in real-life circumstances such as military surveillance, rescue operations or post-disaster search, and creating a map for unknown terrains. With the widespread use of drones, it has also brought legal sanctions; for example, it is seen that in many countries around the world, legal regulations have gradually introduced restrictions on the usage of drones (EU Regulation, 2016).

When it comes to UAV, it is not just the flying part; Along with the aircraft itself, different systems such as control systems, navigation GPS systems and security components are as a whole called as "UAS". It is predicted that the estimated market share of UAVs in worldwide between 2015 and 2025 will be approximately 90 billion dollars (Kahveci & Can, 2017). Although the characteristics of UAVs are determined according to their intended use, each UAV may have advantages and disadvantages due to its structure, the usage area and purpose of use. UAVs can be controlled from a central point and managed by a human operator which can be optimized more simply; or human operator is not in the center of the system and devotes his/her attention to the holistic management of the system rather than providing direct control of the UAVs. UAVs can have an autonom decision making and therefore complexity of the problem becomes higher (Korkmaz et al. 2015). Besides, autonomy of the UAVs can differ and can be categorized in different levels due to human pilot support, environmental independency or use of equipments (Beaudoin et al. 2011).

UAVs can be used in the following areas:

- Military purposes such as attack, combat rescue, surveillance, and reconnaissance
- Forensic applications such as accident, theft, and murder detection

- Agricultural activities such as spraying, botany, plant disease detection, soil measurements (Avdan et al., 2012).
- Logistics applications such as Delivery and Transportation
- Commercial activities such as film-series-advertisement shootings and journalism
- Environmental uses such as atmospheric observation and field mapping
- Mining activities such as area mapping, mine detection, mine gas measurements
- Construction industry areas such as building modelling, bridge and road project design, ground calculations (Villi & Yakar, 2022).
- Safety applications such as traffic monitoring and land security
- Natural disaster situations such as risk calculations and damage assessment of disasters such as flood, landslide, fire, earthquake (Korkmaz et al., 2015).
- Hobby and sports purposes such as individual use, competition monitoring and camera recording (Korkmaz et al., 2015).
- Archaeological applications such as excavation area mapping, historical artifact modelling, historical artifact virtual reality (Villi & Yakar, 2022).
- Healthcare applications such as monitoring cleaning situation or tracking heat maps during the Covid-19 epidemic (Kumar et.al., 2020).

Also, UAVs can have benefits and challenges. The benefits of UAVs may be listed as follows:

i. Regards to their equipment, they can detect and report various dangers; For example, they can detect a military attack in advance or monitor air quality and report dangerous situations such as possible gas leaks. In this way, they enable security and danger detection by monitoring and analysing the environment and real-time data.

ii. It is cost-friendly due to reasons such as reducing labour force, being a more accessible vehicle compared to other aircraft, not requiring investment such as extra operating equipment parts due to its design and reducing the need to use a different hardware vehicle thanks to its equipment such as camera system and GPS.

iii. It helps to reduce possible human injuries and hazards as it reduces the task load on pilots.

iv. Regards to their hardware and features, they can be integrated to be evaluated in different projects, meaning UAVs are compatible vehicles.

v. UAVs are reasonably priced to produce and purchase. UAVs are ten times less expensive than manned aircraft (Karataş, 2020).

vi. Multiple UAVs can be operated by a single ground operator reducing the need and costs of human work. There is no risk of pilot death because the UAV is unmanned.

vii. UAV systems are not restricted by human pilot capacity such as their need of eat, rest, and drink or their exhaustion (Heatherly, 2014).

viii. Due to the fact that UAVs attack suddenly and secretly opponents struggle mentally more as a result of these threats (International Human Rights and Conflict Resolution Clinic (Stanford Law School) And Global Justice Clinic (Nyu School of Law), 2012).

ix. UAVs are particularly helpful in asymmetrical conflicts situations. By way of example, the Turkish Republic declares 15,647 terrorists decease in 2019 after they started to use Unmanned combat aerial vehicle (UCAV) compared to 1,811 deceases in 2009 between 2015 (Karataş, 2020).

The challenges of UAVs may be listed as follows:

i. UAVs can easily be used in attempts to violate privacy or can be manipulated in such a way that they fall into this situation. Although legal regulations try to protect regional and personal privacy, UAV operators may still be misled in unclear situations regarding the use of UAVs.

ii. In case of a systemic, hardware or software malfunction, it may cause damage to living and non-living elements, especially when used in highly populated areas.

Looking at past examples, it is known that due to malfunctions and errors, UAVs have opened fire on civilians uncontrollably causing injuries and losses.

iii. The main targets like terrorist groups are slain by advanced UAV strikes as low as 2 percent of targets, while most victims are innocent people. (International Human Rights and Conflict Resolution Clinic (Stanford Law School) And Global Justice Clinic (Nyu School of Law, 2012).

iv. Resistance to external factors is variable; For example, some UAVs cannot be operated successfully when weather conditions are harsh, and their manoeuvrability may be weakened.

v. It is not easy to produce a high-performance UAV; It must have a design that can meet all requirements and also maintain the necessary aerodynamic properties and take-off mass. There are indicators that have limits that a vehicle must comply with in order to be a UAV, such as mass and degree of manoeuvrability.

vi. Causing deaths or causing great damage by performing remote surgery can blunt human ethical values. “Some people associate drone warfare to PlayStation games, asserting that killing with drones dehumanizes operators” (Shkurti, 2016).

vii. UAVs are more vulnerable to cyber-attacks than normal aircraft, and in possible attacks, control may be taken over by the opposing side.

viii. When controlled remotely, dangers around UAVs may not be easily noticed. Since the operator is not directly in the field of duty, their perception of dangers may not be clear enough. (Karataş, 2020).

2.2. UAV Routing Problems

Within the context of Unmanned Aerial Vehicles, the routing problem is a major difficulty that encompasses both practical applications and technological complexities. Unmanned Aerial Vehicles become increasingly popular in a variety of industries, ranging from mapping and delivery to agriculture and surveillance. The key to maximizing these vehicles' capabilities and maintaining their integration into a variety of contexts is their effective navigation. UAV routing involves several different factors, including avoiding obstacles, saving energy, achieving mission-specific goals, and adhering to regulations. It's critical to comprehend and solve the key points of drone routing issues as they go from being only recreational devices to being essential parts of business and industrial processes.

Essentially, UAV routing is type of a vehicle routing problem, which can be specifically named as “Unmanned Aerial Vehicles Routing Problem (UAVRP)”. It is a subset of the larger vehicle routing problem concept which focuses on determining the best paths for UAVs under some limitations while it is on the allocated mission and destination (Thibbotuwawa et al., 2020). In the literature, UAV routing has been studied in two different ways. In some examples, classical vehicle routing and UAV have been combined and UAV-Truck routing studied have emerged (Young Jeong & Lee, 2023; Kitjacharoenchai & Lee, 2019; Karak & Abdelghany, 2019). Accordingly, while the vehicle is routing to some specific points, the UAV comes into play and UAV-specific route is planned through the vehicle to the destination point. On the other hand, there are also studies specific to UAV that involve only routing the UAV without another vehicle intervention. It is seen that some certain methods are preferred in the literature according to the aim of the studies. Table 2.1 summarizes some example studies on drone routing.

The UAVRP contains distinctive features such as 3D routing, adaptive real-time optimization, multiple objective functions, and other detailed UAV-specific parameters. These characteristics require special consideration and customized strategies to overcome the difficulties that UAV routing brings. With the increase in use of UAVs, risk possibilities that need to be taken into consideration arise. The wide range of uses of these autonomous aerial systems, it is critical to find solutions to the routing challenges that UAVs confront with. This situation requires attention not only to the routing of UAVs but also to the danger factors they may be exposed to. When drone routing problems in the literature are examined, it is seen that some studies focus only on route optimization, while some studies address risk factors.

For example, Değirmen et al. (2018), made a route planning using UAV in order to assess damage level when reaching those disaster areas is not possible. To determine the stations to be used for surveillance for disaster areas, the clustering methos was applied and they purposed a mathematical model. Applications were made with these models and the results were evaluated.

Authors	*Year*	*Methodology*	*Optimization Target*	*Number of UAVs*
Zhang et al.	2020	A* Search Algorithm	Route Optimization	Multiple
Kim et al.	2021	Optimal Routing Algorithm	Route Optimization	Multiple
Peng et al.	2019	Hybrid Genetic Algorithm	Route Optimization	Multiple
Zhang et al.	2022	Q-Learning Algorithm	Maximum Utility Routing / implementing intelligent routing in a cognitive UAV	Multiple
Sutton et al.	2021	Reinforcement Learning	Path planning in dynamic environments	Single
Bellman et al.	2019	Dynamic Programming	Energy-efficient UAV path planning	Single
Karakaya & Aydoğdu	2018	Hybrid Simulated Annealing and Tabu Search Algorithms	Efficient and optimized task completion in UAV path planning	Single

Table 2.1. Example Studies on Drone Routing

UAV flights may include additional risk factors based on their usage area; observation points in enemy territory for UAV routing problem has been determined in the thesis titled "Unmanned air vehicle routing with multiple objectives" written by Daşdemir, E. (2021). It is intended to minimize the total flight distance of UAVs while performing tasks and to maintain confidentiality according to the task. In order to achieve this, mixed integer the programming model was proposed in this study and then a hybrid algorithm was developed for the solution.

Tezcaner Öztürk and Köksalan (2023) suggested an algorithm to minimize travel distance of UAVs and possibility to be detected by radar systems. In line with these two objective functions, they developed a problem model of UAVs to be able to route in continuity space.

Another significant risk is communication failure; Wang et al. (2020) mentioned that communication problems can lead to collisions and accidents. A problem in communication may bring about problems in other areas due to the fact that it is still challenging to guarantee high dependability, reduced latency, and optimal consumption of energy when managing and interacting with the swarm (Iqbal et al, 2022). Problems in telecommunication can significantly affect the entire UAV system and its collective actions (Fabra et al., 2022). For example, a communication problem in a UAV swarm that undertakes a search and rescue mission in a disaster area may cause 2 or more members of the swarm to have an accident or collide in the air, especially in a mission area where there are moving objects, or the field of view is limited.

Additionally, vulnerabilities can occur in UAVs due to cyber-attacks. For instance, Hilldmann et al. mentioned that UAVs which conduct monitoring missions like spying could have security weaknesses and encounter attacks like Sybil attacks that might threaten the UAVs' data transmission and collaboration. This vulnerability might allow opponent to have unforeseen access to private data of the UAVs (2019). Another difficulty encountered is ensuring and maintaining coordination; for example, when UAVs are used to monitor the condition of the crop in a large area such as an agricultural field, it is possible to encounter coordination difficulties such as areas that the UAVs are not scan or overlap in a certain area (Nguyen et al., 2021). Moreover, areas where obstacles are many and variable, such as urban areas, can also pose a danger to the UAVs; in the absence of a good obstacle detection system, UAVs may fail to escape from these obstacles and an accident may become inevitable (Fabra et al., 2019).

According to the Alotaibi (2014), one of the most crucial risks in the military field is that the UAV can be forced to abandon or even terminate the mission as a result of being exposed to enemy attacks and threats. In his thesis, Alotaibi aimed to determine the optimal route for UAV under the attack risk, he defined 2 mixed integer linear programming. To solve these problems, The Branch and Cut and Price (BCP) methodology is preferred. As a result of this study, the UAV should visit the most important targets while minimizing the number of waypoints visited.

Pfeiffer, Batta, Klamroth and Nagi (2007) emphasize that unmanned aerial vehicles are vulnerable to multiple risks during navigating through dangerous areas. The two biggest risks to unmanned aerial vehicles are man-portable air defense systems and anti-aircraft weapons; both systems can detect and strike aircraft. The purpose of this research is to analyze a number of UAV path planning-related complications, such as calculating the minimum risk paths, investigating the relationship between traveling time and risk through bicriteria optimization. Concerns emerge around the possibility of cyberattacks against UAVs and their control systems in addition to the possibility of UAVs crashing with other aircraft or objects. Concerns related to the rights of citizens and privacy are also raised using UAVs for surveillance (Thibbotuwawa et al., 2020).

Kara, Yumuşak and Eren (2023) studied on finding most suitable UAV among UAVs to combat stubble fires in farmland. They used criterion weights obtained by analytical network process (AHP) inside of Complex Proportional Assessment (COPRAS) method and interpreted it through different scenarios.

On the other hand, the difficulty of geographical conditions also has a significant impact on UAV routing studies. In her study, Elmas (2019) aimed to deliver medical aid to villages in hard-to-reach places by UAV and to ensure that the medical product carried was delivered quickly and without damage. The aim is to minimize the time it takes to transport blood samples from villages in this region to a specific hospital. A capacity-constrained vehicle routing mathematical model is presented. MATLAB is used to modelling this problem. This study determines the best route for UAV in the determined region under different modeling.

Chowdhury (2018) carried out a study to keep the inspection and surveillance costs of disaster areas low after natural disasters. Factors such as the duration of the drone fleet's stay in the air and its battery life were considered. Adaptive Large Neighborhood Search as a methodology (ALNS) algorithm and Modified Backtracking Adaptive Threshold Accepting (MBATA) were preferred and the results showed that MBATA produced highly effective results in a reasonable time. At the end of the study, the calculations were applied to a real-life example in Mississippi State to model the proposed method.

Multi-objective route planning for Unmanned Aerial Vehicles is the main topic of the doctorate thesis written by Daşdemir in 2021. Three investigations were carried out: one deals with UAV route planning in hostile areas; the other extends it to optimize collecting information and the third approaches is a multi-objective, multi-connection orienteering problem. The process entails creating a hybrid algorithm that combines a comprehensible mixed-integer programming model with a heuristic route search, as well as a preference-based multi-objective evolutionary algorithm. In the initial study, the challenge of optimizing a UAV's route in a hostile area, A specialized preference-driven multi-objective evolutionary algorithm (MOEA) was applied to find the optimal target and trajectories order. The second study expanded the scope by incorporating an additional objective which is maximizing information collection during the operations. The algorithm's applicability has been proven by the Colorado investigation.

Just as risk-based studies have been conducted in the literature, studies have also been carried out in the literature according to the characteristic of the problem. For example, UAVs are vehicles with versatile mobility, but the movement of the UAV can be restricted depending on the structure of the mission area and the location of the mission points. In his thesis Daşdemir (2021) mentioned that when the task area is districted with the grid structure, the movement diversity of the UAV is restricted. Tezcaner Öztürk and Köksalan (2023) were also studied about routing UAV with grid structure. On the other hand, when the mission area is considered as a continuous area, it has been observed that the UAV movement diversity increases, but the problem also becomes more complex; On this subject, Pfeiffer et al. (2007) and Tezcaner Öztürk and Köksalan (2023) studied UAV routing. Additionally, one of the most important parts of UAV routing is waypoints; waypoints are intermediate points between locations to be visited on the route. These waypoints are used when creating the best route for the UAV and different methods can be followed to create waypoint. The use of waypoints has been handled differently in routing problems; for example, while a predetermined point can be chosen as a waypoint, such as Moskal and Batta (2019), by dividing the task area into a certain part and accepting the middle point of these parts as a waypoint. Besides, Study conducted by Nikolos et al. (2003) is an example of searching for the most optimal point to be candidates for waypoint can also be seen.

Peng et al. (2019) used Genetic Algorithm for ground vehicle-multiple UAV usage in logistics delivery. Package delivery to different locations was studied with a one vehicle and more than one UAVs; for creating a rotation that minimize the total delivery time with using genetic algorithm. As the result of the study, two basic criteria were taken; save time and save distance. While time includes leaving the warehouse and completing distribution to all recipients, distance includes the distance travelled by both the ground vehicle and the drones. In this study, the results of the proposed algorithm were compared with other results.

2.3. Swarm Intelligence Algorithms for Solving UAV Routing Problems

2.3.1. Swarm Intelligence Algorithms

Metaheuristic Algorithms are inspired by the nature, they simulate natural movement and behaviour to solve challenges of human design systems (Er, 2010). There are various categories in metaheuristic algorithm, one of them is called “Swarm Intelligence Algorithms”. Swarm intelligence algorithms have started to play an active role particularly in autonomous systems, that is, self-managing systems independent of humans and also determination of the working principles of autonomous devices.

Swarm Intelligence (SI), which is a collective behaviour of decentralized, self-organized systems, natural or artificial. It is inspired by the behaviour of social animals such as ants, bees, birds, and fish, which exhibit complex and intelligent group behaviours without centralized control. In SI, individual agents interact with each other and their environment to achieve a common goal, such as finding the optimal solution to a problem (Sun et al., 2020).

The idea of swarm intelligence has a long history; In his book Politics, Aristotle points out a concept that can be considered the basis of Swarm Intelligence; "The Wisdom of the Crowd". Aristotle mentioned this concept as *"For the many, of whom each individual is not a good man, when they meet together may be better than the few good, if regarded not individually but collectively, just as a feast to which many contribute is better than a dinner provided out of a single purse.”* (Waldron, 1995). In other words, the knowledge and decision-making skills of the community should be positioned at a higher point than that of each individual within that community. It seems that the swarm intelligence applications which are developed day by day are actually quite compatible with this approach; Swarms act as a community, communicate with each other and transfer data. Therefore, they follow a more accurate and efficient decision-making process by being aware of the information each other collects and the situations they are exposed to. Living communities tend to act together to accomplish tasks within their needs and goals to survive.

Various swarm intelligence algorithms exist in the literature. Some of the examples are as follows:

- Ant Colony Optimization (ACO) (Aksaraylı & Pala, 2018)
- Particle Swarm Optimization (PSO) (Wang & Tan & Liu, 2018)
- Firefly Algorithm (FA) (Johari et al. 2013)
- Artificial Bee Colony Algorithm (ABC) (Öztürk et al. 2012)
- Bacterial Foraging Algorithm (BFA) (Wei et al., 2012)
- Cat Swarm Optimization (CSO) (Ahmed et al., 2020)

The foundations of Ant Colony Optimization (ACO) were developed by Dorigo in 1992; a flock that imitates finding and taking the found food to the nest by the shortest route (Aksaraylı & Pala, 2018). In nature, ants leave odour particles called pheromone trails on the route they passed. Initially equal number of ants are sent to all possible routes. Pheromones evaporate over time and less ants travel long distances per unit of time, there are fewer pheromones in these paths. Considering the pheromone density, which is in their new routes, they prefer shorter routes with more pheromone numbers (Aksaraylı & Pala, 2018). Thanks to the traces left by the effect factor due to the changing environmental conditions, the whole system becomes aware of this effect and rearranges itself (Kaynarkaya & Çağdaş, 2020). Besides, The Travelling Sales challenge (TSP), which is the challenge of determining the shortest complete route that visit every location just once and returns to the originating location (Erol Bingüler et al., 2012). There is literature examining the ant colony algorithm together with many TSP applications; because the aim in TSP is to find the shortest optimal path and the ant colony algorithm creates an algorithm for finding the shortest distance inspired by the ants.

The Particle Swarm Optimization (PSO) is a population-based stochastic optimization algorithm inspired by the intelligence group dynamics of several species, such as flocks of birds or fish schools. It has undergone numerous improvements since its debut in 1995 by the Jim Kennedy (Wang & Tan & Liu, 2018). The PSO algorithm is built on individuals sharing social information. Process of looking for information is carried out by the individual who make up the population over a number of generations. To every single individual, a particle is a small group of particles, whereas a swarm is a large group of particles. Each individual, his position in the herd by making use of his previous experience adjusts to converge towards best positioned individual. Best value in the herd while individual with the current status is called the global best, the individual's best value is called local best, and these values are stored in memory in the algorithm. Another reason is that the position of the herd is brought closer to individual with the best position in the herd. Expression is based on convergence (Bastı & Özçakar, 2012). The PSO can be seen that for the route planning for UAVs.

Basically, the firefly algorithm refers to fireflies that tend to select the one closest to them and the brightest in comparison to them. This is because fireflies do not have sex and the selection criterion is only affected by distance and brightness. The brightness of the fireflies should be linked to the connected problem's optimisation problem. Because of their appeal, they can separate into subgroups, and every cluster swarms around the model parameters. (Johari et al. 2013). According to Sahu, Panda & Padhan (2015), "*FA is a population-based algorithm developed by Yang. Fireflies are characterized by their flashing light produced by biochemical process bioluminescence.*" FA applications are used for data clustering and data classification problems.

One of the most popular algorithms among the Swarm Intelligence is the Artificial Bee Colony (ABC) which was created by studying honeybee swarm foraging dynamics. One of the best examples of swarms that use the ability to act together and make decisions as a community is bees; They work together, have a closed network within themselves, and are able to transfer their own intelligence to an extraordinary degree to the group (Rosenberg et al., 2018). The ABC algorithm is well-known for its performance in numeric optimization problems and classification approaches (Öztürk et al. 2012).

The aim of the study written by Lei et al. (2022) is to address the Vehicle Routing Problem with Drones (VRPD) by proposing a new algorithm named Dynamical Artificial Bee Colony (DABC) to minimize the overall operational cost of VRPD. The problem statement revolves around the limited application of Artificial Bee Colony (ABC) to VRP and its variants, including VRPD, which are not effectively solved by existing methods. The results of the study demonstrate that DABC produces best 37 new solutions and outperforms other algorithms in terms of solution quality and computational efficiency, thus showing promising advantages for addressing VRPD.

According to the research of Güney and Başbuğ (2008), The Bacterial Foraging Algorithm (BFA) is mentioned as a new evolutionary computation technique based on the foraging behaviour of Escherichia (E.) Coli bacteria in human intestine. It can be said that BFA is commonly preferred to determine the shortest path for the networking such as subway networking or highway networking.

Cat Swarm Optimization (CSO) is developed in 2006 by Chu and Tsai. It is derived from natural cat behaviour and includes a unique modelling approach for the explorative and exploitative stages (Ahmed et al., 2020). Cats appear to be sedentary and spend the majority of its time by sleeping. Nevertheless, their awareness is quite intense throughout their sleep, and they are highly careful and alert for what's happening around them. As a result, they are continuously and carefully monitoring their surroundings, and when they spot a target, they immediately begin moving towards it. As a result, the CSO algorithm is built on integrating these two major cat behaviours.

Other algorithms also appear in the literature from time to time, and the mathematical encodings behind these algorithms continue to be explained (Varol & Alataş, 2016).

2.3.2. Literature of Swarm Intelligence Algorithms in UAV Routing

The route planning problem for Unmanned Aerial Vehicles has additional constraints such as flight altitude, areas not to be crossed, various natural conditions, geographical formations, and technological capacities. These are the constraints which are not included in other problems such as Travelling Salesman Problem (TSP) or Vehicle Routing Problem (VRP). For this reason, there are objectives in UAV routing problems that classical methods cannot answer well enough. At the point where classical methods are insufficient, swarm intelligence and swarm intelligence algorithms have been used. These algorithms inspired by nature are frequently used in UAV routings today and studies are being carried out on them. When a UAV receives a command, it executes that command, but in cases where it does not receive or cannot receive a command, that is, there is no human control, it must be able to collect information from its environment and take an action accordingly so that the mission can continue (Frantz, 2005).

UAV routing problem is a high-dimensional Non-Polynomial Hard (NP-hard) problem. Swarm intelligence algorithms are very successful to solve NP-hard problems due to their ability to effectively explore larger searching space and gather near-optimal solution. Different swarm intelligence algorithms were applied to solve UAV routing problems in the literature (Hildmann et al., 2019; Ananthi et al., 2022). Table 2.2 provides a summary of example studies from the literature on the use of swarm optimization in UAV routing problem.

Yakıcı (2016) addressed the challenge of routing and location the UAVs effectively by considering maximization of total ratings that the UAVs gained after visiting target spots on flight routes. The author presents an integer linear program (ILP) and ant colony optimization (ACO) approach to solve the combinatorial problem. The computational experiment shows that the suggested approach surpasses conventional solutions. This shows that applying the suggested strategy results in a noticeably higher-quality solution. The study also showed that the suggested ACO approach may quickly arrive at optimal or almost optimal solutions in a short time while ILP formulation is inadequate when the problem size become larger.

Adriyansyah et al. (2023) used Artificial Bee Colony Algorithm for path planning to determine the fastest route for a drone to navigate through a coffee plantation. The methodology involves the use of 4 drone equipped with GPS and 4K camera and implementing ABC Algorithm using MATLAB programming. The study provides a comparison between the best route generated by ABC algorithm and the manual calculation results. The results generate optimal routes for the drone to navigate through the coffee plantation successfully while monitoring the ripening level of the crops. The research contributes to the field by demonstrating the practical application of the Bee Colony Algorithm in path planning for drones, specifically in the context of agricultural monitoring in a coffee plantation (Adriyansyah et al., 2023). Lamont et al. (2007) used evolutionary algorithms for optimum UAVs task scheduling and navigation. The findings showed how efficiently this strategy worked to produce beneficial, multi-objective task scheduling and navigation for UAVs. Sharma and Ghose (2009) concentrated on employing particle swarm optimization, to prevent collisions among UAV groups. The goal behind this research was to fulfil UAVs' technical requirements for avoiding accidents, and the outcomes demonstrated how effectively swarm intelligence methodologies can be applied to provide secure and effective cooperation across UAV groups.

Other than that, for UAV-assisted IoT data capture deployment optimization, Chen et al. (2020) suggested a programming technique based on swarm intelligence optimization. The objective of this investigation was to use swarm intelligence to improve UAV deployment of internet of things (IoT) information collecting. The findings showed how successful the suggested strategy worked to achieve optimum deployment for UAV-assisted IoT data collecting by minimizing distance. An additional example comes from the study done by Jacob & Darney (2021), which improved wireless network routing by applying the artificial bee colony optimization technique. A wireless environment-specific model had to be created, performance had to be optimized using the right tools, and routing had to be improved by carefully choosing performance metrics. The outcomes demonstrated how well the artificial bee colony optimization technique works to improve wireless network routing.

Xu et al. (2022) created a multi-discrete wolf pack algorithm-based assignment of work technique for UAVs. The goal of that research was to use swarm dynamics to maximize assignment of tasks inside UAVs. The outcomes demonstrated what extent the multi-discrete wolf pack algorithm worked to achieve effective job assignments for UAV swarms. A route planning technique for multi-UAV formation reunion based on decentralized cooperative particle swarm optimization was presented by Shao et al. (2019). The aim of the study was to provide every drone in the swarm with a secure and capable of flying pathway. The outcomes showed the success that the distributed cooperative particle swarm optimization method is at path planning for multi-UAV formation reunion. Table 2.2. summarizes some example studies on drone routing which includes swarm intelligence algorithms.

Authors	***Year***	***Methodology***	***Optimization Target***	***Number of UAVs***
Yakıcı	2016	Ant Colony Optimization	Maximizing Prize Collecting	Multiple
Lei et al.	2022	Dynamical Artificial Bee Colony (DABC)	Minimizing operational cost	Multiple
Adriyansyah et al.	2023	Artificial Bee Colony Algorithm	Determining Fastest Route	Single
Lamont et al.	2007	Evolutionary Algorithm	Optimum Task Scheduling and Navigation	Multiple
Sharma & Ghose	2009	Particle Swarm Optimization	Preventing Collisions Among UAV Groups	Multiple
Xu et al.	2022	Multi-Discrete Wolf Pack Algorithm	Maximizing Assignment of Tasks	Multiple
Peng et al.	2012	Particle Swarm Optimization	Online Route Planning	Single
Yan et al.	2021	Particle Swarm Optimization	Optimization Efficiency	Multiple
Ding & Li	2021	Particle Swarm Optimization	Real-Time Monitoring	Multiple
Ananthi & Jose	2022	Artificial Bee Colony Algorithm	Optimizing Data Communication Routes	Single
Durand & Alliot	2009	Ant Colony Optimization	Air Traffic Conflict Resolution	Multiple
Saied et al.	2019	Artificial Bee Colony Algorithm	Obstacle Avoidance and Collision Prevention	Multiple
Shihab et al.	2022	Hybrid Artificial Bee Colony Algorithm	Reducing Total Search Time and Path Length	Single

Table 2.2. Example Studies on Drone Routing Using Swarm Intelligence Algorithms

Sixu et al. (2022) used ABC method to route UAVs with an emphasis on creating a cluster routing protocol involving a moving base station. In software-defined wireless sensor networks, extending the network lifespan while maintaining energy balance was the main objective. In order to optimize the cluster routing protocol, the research combined the ABC method with particle swarm optimization. The results demonstrated how well this strategy worked to achieve energy consumption balance and extend the network lifetime in wireless sensor networks.

Ananthi & Jose (2022) tried to find the best routing system as possible for the use of UAVs in medical applications. The Artificial Bee Colony-based UAV Routing (ABCUR) algorithm was designed to make it easier for patients and physicians to communicate effectively about medical data. The process included customizing the ABCUR algorithm's architecture and execution to satisfy the demands of UAV routing in the healthcare industry. The outcomes demonstrated the accuracy of the ABCUR methodology may meet demands for communication in healthcare applications.

3. METHODOLOGY

This section explains the methodology of the thesis in detail. Overview of the proposed approach, working principle of Artificial Bee Colony Algorithm, definition and mathematical model of the problem, and the structure of the proposed hybrid approach are given in subsections.

3.1. Overview of the Proposed Approach

Especially in crowded cities, product deliveries may be difficult due to many external factors such as traffic density. Therefore, there may be delays in delivery of packages. Moreover, it is important to be able to deliver packages to areas that are difficult to reach by vehicle. For these reasons, applications have recently been made to make package deliveries using drones. Many large companies such as Amazon, DHL and UPS are carrying out deliveries via drones. When real life applications and literature studies are examined, it is seen that there are many studies and applications on drone delivery. However, the majority of these studies include examples of using multiple drones, each drone delivering to one customer, or using a delivery truck as a warehouse, going back and forth to each customer and picking up the loads from the truck one by one. Truck-drone systems are used for long-distance distribution, while single delivery with a single drone is used for shorter-distance distribution. However, this may cause loss of time or high operational costs. Studies have shown that it is possible for a drone to carry more than one load. Using a single drone for deliveries is a beneficial practice as it reduces the operational costs for each delivery, prevents drone confusion and crowding in the air, and reduces the number of returns to the warehouse after each shipment (Lee et al., 2022).

The aim of the thesis is to develop a swarm-intelligence based optimization approach to solve the routing problem of a single drone under various risks and threats. Optimization is a collection of operations that finds the best solution for a given problem under some constraints, in realizing the goal-oriented criteria (Alataş & Varol, 2016). Metaheuristic algorithms, one of the most popular concepts of today, are among the methods that have become widespread in optimization. Metaheuristic algorithms are one of the evolutionary computation techniques and can adapt themselves without requiring changes on the problem of interest, as in classical algorithms (Aydin, 2009). Swarm Intelligence Algorithms are popular metaheuristic algorithms.

The proposed model aims to create the shortest route by visiting certain destination points for a selected drone model. In addition to traditional studies in the relevant literature, our model also aims to minimize the total risk level that drone can be exposed and combines minimizing risk level and minimizing the total distance objective functions. Hence, the model helps increase the competence of UAVs in air operations.

The problem is formulated for a single drone designed to deliver packages to multiple customers during a single flight. In addition, a new approach to the problem, harmony based artificial bee Colony algorithm with 2-Opt is introduced (2-Opt Harmony Based Artificial Bee Colony- HABC-2O). The hybrid structure aims to improve the capabilities of the basic ABC algorithm.

The results of the proposed model are compared with the classical ABC algorithm and Ant Colony Optimization (ACO) algorithm. Ant colony algorithm is another swarm intelligence algorithm used in drone routing. It is applied to the same problem and compared with the proposed model. Ant colony algorithm is an optimization algorithm discovered by Marco Dorigo in 1992. In this practice, the algorithm mimics the foraging behavior of ant colonies. When ants move towards the food sources they find, they determine the location of the source by releasing a secretion called pheromone. ACO is a meta-heuristic algorithm developed to solve complex optimization problems and known to be used in TSP problems.

3.2. Artificial Bee Colony Algorithm

Since its introduction by Karaboğa in 2005, The Artificial Bee Colony (ABC) method has shown beneficial results in many areas, such as clustering analysis, function optimization challenges, and route planning of vehicles (Ding et al., 2015). The ABC algorithm is well-known for its good performance in numeric optimization problems and classification approaches (Ozturk et al. 2012). In other words, "*The ABC algorithm is capable of handling multi-modal fitness functions with relatively few parameters to be adapted*" (Kaba & Kiyak, 2020).

As it is mentioned in the Article written by Pham and Castellani in 2015, ABC can be used in different ways to find solutions for the many engineering problems like pattern classifier training, dynamic control problems, machine shop scheduling, robotic swarm coordination, non-linear model identification and control system tuning. Moreover, ABC is also used to determine the joint movement of mobile robots and continuous calibration with a multi-master method to find the optimum position and to identify suitable routes which must be followed by the mobile robots during the completion of a target task (Tosunoğlu & Kurt, 2019).

3.2.1. Nature of the Bee Colonies

In nature, there is a division of labour between the bees in the colony (Baykasoglu et al., 2007). Specific bees are assigned to specific jobs. With this division of labour, bee colonies can be organised without a central bee, i.e. without a manager or a central control point. In fact, this shows that bee colonies have the most important features of swarm intelligence algorithms: division of labour and self-organisation. The main purpose of bee colonies is to find food, i.e. nectar or pollen. For this purpose, bee colonies develop a system within themselves, and it is possible to divide this system into 3 elements as the most basic elements. These are food sources, worker bees on duty and worker bees without duty. The tendency of the system can be mentioned under 2 headings as tendency towards the source and abandonment of the source.

In his book Karaboğa (2020) explained the 3 main elements of the system as follows:

i) Food Source: The first of the 3 elements of the system is the food source which is the supply points where bees collect nectar to produce honey. Criteria such as the quality of the nectar, quantity of the nectar or distance to the hive provide information about the source.

ii) Employed foragers: The employed foragers are responsible for bringing nectar from known sources. These bees provide information such as the location and quality of the food sources they visit for the other bees in the hive by using specific movements.

iii) Unemployed foragers: The Unmployed foragers consist of bees that search for resources and have not yet been assigned. Unmployed foragers may tend to exhibit 2 types of behaviour; the first of these is to wait in the hive and learn the locations of food sources from the dance movements of the worker bees; These bees are called "onlooker bees". The other tendency is that they act with their instincts depending on an external factor and search for a food source, these bees are called "scout bees". However, the number of scout bees is quite low compared to others; on average, they constitute 5% to 10% of the entire hive (Karaboğa, 2020) and the half of the hive is filled with worker bees (Tosunoğlu & Kurt, 2019).

Considering the ecosystem of bee colonies, we can divide it into 3 areas: hive, food source and dance area (Baykasoglu et al., 2007). In this system, the dance area is of great importance because it is necessary for the collective information sharing of the bees in the hive. When an employed forager bee arrives at the dance area, onlooker bees follow her dance movements while also collecting information about the food source by touching their antennae. This dance is specifically called as “a waggle dance” (Karaboğa, 2005). The dance movements performed changes according to information given. While the sweetness of the food affects the dance the most, other factors such as distance, ease of access, and weather conditions are also effective. Onlooker bees make inferences about the sources by looking at the dancing employed bee and probably chooses the best source in her opinion (Karaboğa, 2005).

It is possible to divide employed bees into 3 categories named EB1, EB2 and EB3 as in Figure 3.1. EB1 is the bee that brings food from the food source to the nectar area and then goes to the dance area and shares information about the food source. In EB2, bees only collect the food from the source and bring it to the nectar area, they do not go to the dance area and share information about the food source. Bees that no longer visit the food source due to decrease/depletion of food or deterioration in its quality are called EB3. In other words, they are 'abandoning the source'. After they permanently leave the source, they become a ‘scout bee’ (Karaboga & Gorkemli, 2014). Unemployed bees are divided into two, scout and onlooker bees. Onlooker bees are bees that monitor the dance area and collect information about food sources based on the dances performed there. In addition, scout bees are bees that randomly search for food sources according to a natural stimulus and their instincts and try to find potential food sources.

The direction and distance of the food source relative to the hive is crucial. Bees must use the concepts of direction and distance to find the source with the information about the food source learned in the dance area. Naturally, bees find their direction according to the sun. For this reason, they calculate direction by computing the angle between their own orbit and the sun's rays. Even in cloudy weather, due to the structure of their eyes, they see the rays in polarized form and know the location of the sun. Besides, distance measurements are related to the energy they spend. The more energy it consumes, the farther away the source is. Therefore, they adjust their flight patterns and altitudes according to the load and distance they carry. Therefore, just knowing the location and quality of the source is not enough; The distance of the source and the energy to be spent are also of great importance.

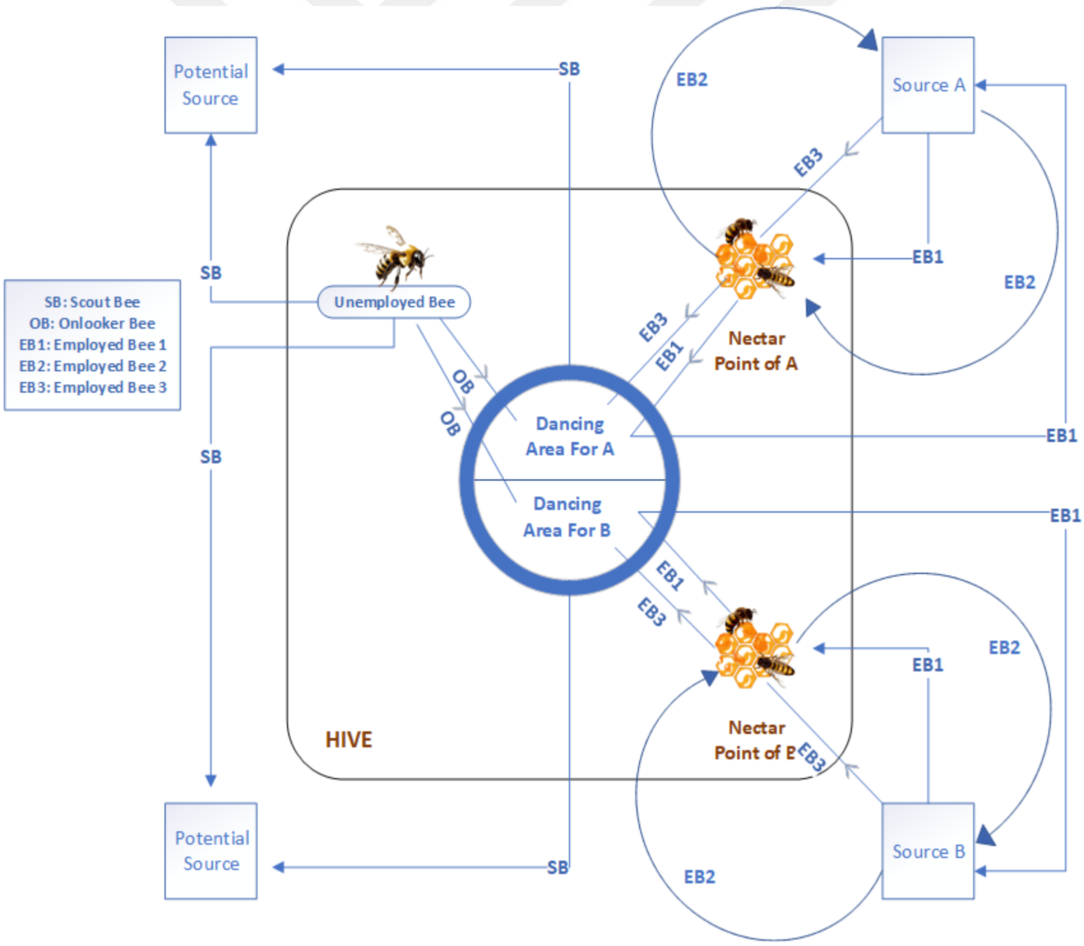

Figure 3.1. Basic Composition For Behavior Of Bees in The Hive

(Adapted from Karaboğa, D. (2011). *Yapay Zeka Optimizasyon Algoritmaları*. Ankara: Nobel Yayın Dağıtım, p. 231.)

To summarize the organization in bee colonies, positive or negative feedback can be received (Karaboğa, 2005). In positive feedback, as the nectar in the food source increases, the visits of onlooker bees also increase. On the contrary, in negative feedback, a decrease or poor quality in the food source reduces the number of bees visiting the source and the use of the source. Additionally, information can be shared in the field of dance and multiple interactions can occur between bees. Finally, scout bees can search for random resources and make discoveries (Karaboğa, 2005).

3.2.2. Modelling of the Artificial Bee Colony Algorithm

In the modeling of the classical ABC algorithm, some basic assumptions have been made for the sake of simplicity. In ABC algorithm, bees are divided into 3 main groups; employed bees, scout and onlooker bees. In general, the population of hive divided into 2 which are employed bees and onlooker bees equally distributed in the beginning. In addition, it is accepted that only one employed bee is employed for each food source and each employed bee can only work in one source. This means that there are as many food sources as there are employed bees. When the food source used by an employed bee runs out, that bee turns into a scout bee and starts looking for other potential food sources. While source location expresses the possible solution; nutrients abundancy in the source indicates fitness for this solution (Karaboga & Gorkemli, 2014). Figure 3.2 demonstrates the flow of the ABC method.

In order to maintain both discovery and extraction throughout the search process, the mathematical model of the method includes use of search equations and solution updating equations. When the basic code of the ABC algorithm is examined, it is seen that the bees are divided into 3 main tasks. These are employed bees, onlooker bees and scout bees. Worker bees leave the hive to go to the food source they remember, and when they return, they dance to give information about the source. Onlooker bees are the bees that decide on the source to go by watching the dances performed. When the algorithm is examined, it is seen that onlooker bees make choices with a probability determined according to the quality of the resource. Scout bees, on the other hand, are bees that find new resources regardless of the guidance or experience of any other bee, consume the resource, and then turn into an employed bee. The purpose of having scout bees is to discover new resources besides known resources. According to the algorithm, in the first step, all bees are scout bees, and they produce random solutions by searching for a random food source.

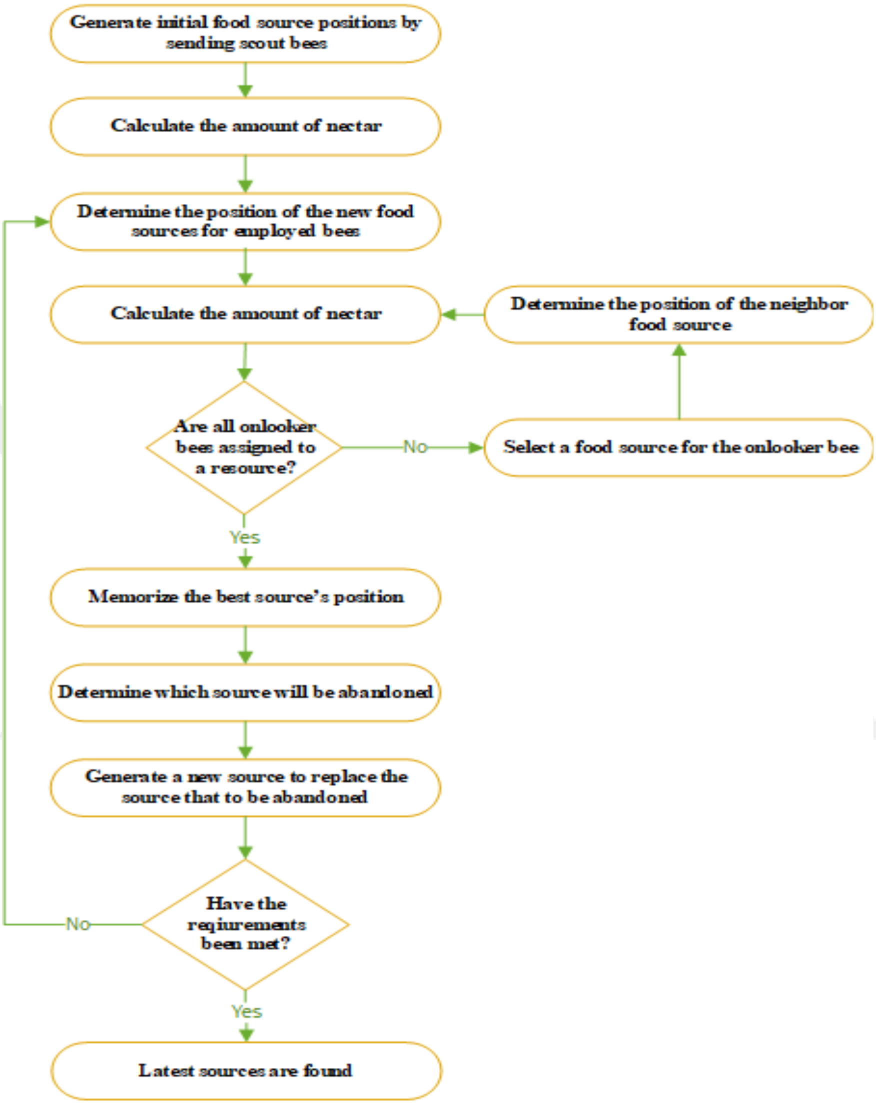

Figure 3.2. Flow Chart of the ABC Algorithm

(Adapted from Yuce, B., Packianather, M. S., Mastrocinque, E., Pham, D. T., & Lambiase, A. (2013). Honey Bees Inspired Optimization Method: The Bees Algorithm. *Insects*, *4*(4), 646–662. https://doi.org/10.3390/insects4040646)

In the following steps, when food resources begin to run out, the employed bee that consumes the resource turns back to the scout bee. The algorithm controls the depletion of the food source by defining a limit parameter. Accordingly, by counting the number of attempts to improve that solution for each solution, it is checked whether the resource (solution) with the maximum number of attempts in each cycle exceeds the predetermined limit value. If the limit value is exceeded, that resource is abandoned, and the resource search process continues with a randomly generated new solution.

The basic algorithmic structure of the ABC algorithm can be expressed as in Figure 3.3. In the initial phase, the food population in the starting position is refereed as *SN* and every food source has a d-dimensional vector to refer candidate solution (Li et al. 2023). The food amount in the starting position is determined randomly. The size of the bee population is half employed bee and other half onlooker bees (Kıran, 2015). Therefore, if SN number of bee are available; it means that FN= SN/2 number of food source can be produced at the beginning. To produce food sources (Eq.1) in Figure 3.3 is used.

In employed bee phase, FN number of bees, that is, half of the colony size, serve as employed bees and discover and evaluate the food sources (solutions) which are equal to the randomly generated FN at the beginning. Each employed bee produces a new solution (food source) in the neighborhood of its current solution as shown above. The fitness value of the new solution is calculated and compared with the existing solution by using equation [3] in Figure 3.3 according to the Greedy Selection Process. If a better solution is found, the current solution is updated. In other words, if new food source is better than the previous one, this new food source's position is memorized by employed bees. Therefore, AC (Abandonment Counter) is reset. If new food source is not the better one, AC is increased by 1.

In onlooker bee phase, onlooker bees make a choice based on fitness values of solutions which were evaluated by employed bees. Same as employed bee phase, onlooker bees create a new solution around the selected solution and the fitness value of this solution is calculated. If a better solution is found, the current solution is updated.

SET iteration = 0

1. Initial Phase

Determining the parameters

SN: Number of bees

FN: Number of initial food source ($\boldsymbol{FN = \frac{SN}{2}}$)

D: Dimension of the problem (number of variables to be optimized)

Boundaries ($\boldsymbol{u_j}$ **and** $\boldsymbol{l_j}$): Upper and lower bound for each variable

AC: Abandonment Counter

$\mathbf{Iteration_{max}}$: Maximum number of iterations

limit: limits the depletion of the food source

$\boldsymbol{\phi}$: Random number between [-1,1]

$\boldsymbol{i}$: Solution index, represent current solution (which is employed bees are working on)

$\boldsymbol{j}$: Component index of the solution shows variable of operated solution.

$\boldsymbol{k}$: Index of another randomly selected solution, must be different from current solution ($\boldsymbol{k \neq i}$)

$\boldsymbol{x_{i,j}}$: ith solution of jth component.

$\boldsymbol{x_{k,j}}$: randomly selected solution of jth component ($\boldsymbol{k \neq i}$)

Initialize the position of food sources randomly considering the borders $\boldsymbol{l_i}$ and $\boldsymbol{u_i}$ by using the equation:

$$\boldsymbol{x_{i,j} = l_j + \mathrm{rand}(0,1)\,.\,(u_j - l_j)} \quad [1]$$

where *i= 1,2,…FN* and *j= 1,2,…D*

For each food source ($\boldsymbol{x_i}$), set the non-improvement counter as zero.

$\boldsymbol{AC_i}$ = 0

REPEAT *for every i in (1,2,…,FN)*

2. Employed Bee Phase

Produce new food source positions $\boldsymbol{v_{i,j}}$ which is the neighbour of the source $\boldsymbol{x_{i,j}}$ by using the equation:

$$\boldsymbol{v_{i,j} = x_{i,j} + \phi_{i,j}\,.\,(x_{i,j} - x_{k,j})} \quad [2]$$

Calculate the fitness to determine the quality of the source by using the equation:

$$\boldsymbol{fitness\,(x_i) = \begin{cases} \frac{1}{1+f(x_i)} & ;\ if\ \ f(x_i) \geq 0 \\ 1 + abs(f(x_i)) & ;\ otherwise \end{cases}} \quad [3]$$

Apply the Greedy Selection Process between $\boldsymbol{v_{i,j}}$ and $\boldsymbol{x_{i,j}}$ and choose the better one to find which source to continue with.

If the solution $\boldsymbol{x_i}$ has not been developed; increase $\boldsymbol{AC_i}$ = $\boldsymbol{AC_i}$ + 1

Otherwise set $\boldsymbol{AC_i}$ = 0

3. Onlooker Bee Phase

Calculate the the probability values ($\boldsymbol{p_i}$) for the unvisited food source to use in source selection by using the equation:

$$\boldsymbol{p_i = \frac{fitness(x_i)}{\sum_{i=1}^{SN} fitness(x_i)}} \quad [4]$$

Normalize $\boldsymbol{p_i}$ values between [0,1]

Produce random *p* value between [0,1

According to The Roulette Wheel Selection Method,

If $\boldsymbol{p_{i}>p}$;

Use (Eq. 2) and produce a new food source ($\boldsymbol{v_{i,j}}$), compare $\boldsymbol{v_{i,j}}$ and $\boldsymbol{x_{i,j}}$ and choose the better one.

If the solution $\boldsymbol{x_i}$ has not been developed; increase $\boldsymbol{AC_i}$ = $\boldsymbol{AC_i}$+1

Otherwise set $\boldsymbol{AC_i}$ = 0

4. Scout Bee Phase

If Max $(\boldsymbol{AC_i}) >$ *limit* ; change the solution $\boldsymbol{x_i}$ with random generated solution by using equation [1]

Memorize the best solution.

Set iteration = iteration + 1

UNTIL ($\boldsymbol{Iteration_{max}}$ is reached)

Figure 3.3. Pseudo Code of the ABC Algorithm

In scout bee phase, if a solution cannot be improved over a certain number of consecutive cycles (defined with *limit* value), it is abondoned and scout bees are generating a new random solution. At the end of each iteration, the current best solution is updated and saved. The steps are repeated until the maximum number of iterations is reached.

3.3. Problem Definition

In this thesis, a sample application has been made for package delivery for retail companies. In this problem, a warehouse is determined as the starting and returning point for the delivery drone. Warehouse's location and 20 customer delivery point are randomly determined within a selected area in Istanbul's Asian side. The locations of customers are identified randomly to simulate the randomness of orders in the actual life. In addition to customer locations, the drone is designed to fly from a certain height, land vertically on the building where it delivers, drop off the package, then rise back to the same altitude and fly to the next delivery point. Studies have shown that a drone can deliver multiple packages to addresses using electromagnets and different levels of cargo sorting (Lee et al., 2022). For this reason, it was thought that such multi-package single drone deliveries could be applied to drones in real life when appropriate design and conditions are provided and were included in this problem.

The selected warehouse point and random delivery points were marked on Google Maps and latitude and longitude information were determined. Based on this information, a distance matrix between all points was created. The distances between points on the route are calculated using the Euclidian Distance Formula. The drone's descent and ascent movements are also included in the distance formula as the height of destination buildings are different. Since a small area was chosen, the effect of the earth's surface curvature on the distance between points was considered negligible.

Figure 3.4 shows the image of the selected points on Google Map. The delivery points (customers) are numbered between C1 and C20. It is assumed that legal permissions have been obtained to fly drones in this area.

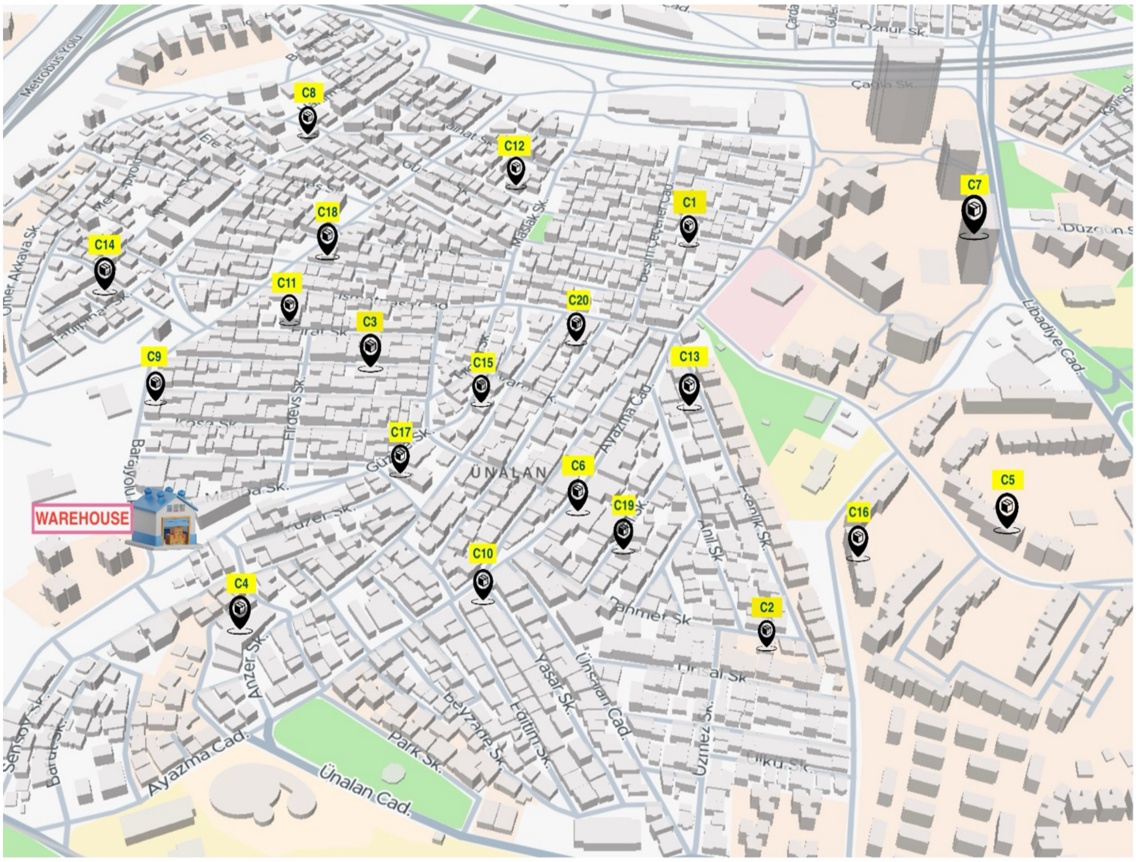

Figure 3.4. Warehouse and Delivery Points Shown on Google Map

A Travelling Salesman Problem (TSP) is created where a single drone picks up the packages belonging to customers from the starting point, which is the warehouse point. The drone visits all customers and delivers the packages. Then it returns back to the warehouse point. For this problem, the DJI FlyChart 30 drone model, which is specially designed for carrying loads, was chosen. The reason for choosing this drone is that while many drones used in the market have low capacity in terms of carrying packages, this drone model is specially designed to carry heavy loads. The DJI FlyChart 30 has a payload carrying capacity of 30 kg and has a flight range of 16 km with full payload capacity (DJI, n.d.). In the research conducted to determine the average weight of customer cargo, it was found that 85% of Amazon cargo consisted of cargo weighing less than 2.27 kg (Lee et al., 2022). For this reason, in order not to exceed the 30 kg load carrying capacity of the drone, it was assumed that the cargo weights of the 20 customers involved in the problem did not exceed a maximum of 1.5 kg. For the route to be created based on the selected drone features, a maximum distance restriction was added; the route to be created should not exceed 16 km, which is the maximum distance DJI FlyChart 30 can fly. The DJI FlyChart 30 drone model is shown in Figure 3.5.

Figure 3.5. DJI FlyChart 30

(DJI, n.d.)

In addition, since the problem under consideration is designed to conduct a drone routing study by taking into account the risks on this route, a maximum risk constraint has also been added to the problem. Some districts in the Istanbul region are particularly popular in terms of bird density. Bird populations in some areas can pose a danger to drones due to buildings that have become habitats and flight points for birds. Birds can pose a flight safety risk to drones. Drones can collide with birds, get damaged, or even crash depending on the extent of the damage. In addition to the possibility of collision, many incidents have been encountered where birds perceive drones as a threat and attack and cause damage. For example, it has been recorded that crows attacked delivery drones or that drones used as lifeguards on the beach were attacked by shorebirds on the beach (Daily Sabah, 2024).

The pilot region chosen for the problem is Ünalan, a region of Üsküdar district. Due to the proximity of this region to the sea, flocks of birds such as seagulls, crowns or pigeons are frequently seen. Therefore, birds were considered as a risk factor for the drone and its delivery applications. In addition, air temperature and wind conditions can also be dangerous for the drone. Very windy weather can be risky for the drone in terms of flight safety, while hot weather can be risky for the drone in terms of battery performance, engine temperature and durability of the drone components. At the same time, air temperature and wind conditions are also factors that affect the bird population. Based on this, a risk scale has been defined in Table 3.1 and Table 3.2 in order to evaluate the effects of different temperature and wind combinations on the bird population and the drone.

	Windy	**Moderate**	**Light**
Hot	3	4	5
Warm	2	3	4
Cold	1	2	3

Table 3.1. Risk Scale for Bird Population According to Weather Condition

	Windy	**Moderate**	**Light**
Hot	5	4	3
Warm	4	3	2
Cold	3	2	1

Table 3.2. Risk Scale for Drone Durability

When determining the risk scale for bird danger in the region, the distances of the customers' location to the sea were calculated. Birds tend to be in areas close to the sea. After calculating the distances of the buildings to the sea, the risk value of each building (the delivery point where the customer is located) was calculated. The formula used in this calculation is shown in the following equation:

$$RB_i = C_1 \, . \, DS_i \qquad [5]$$

Where:

- RB_i is the Bird Risk Value of delivery point i
- C_1 is the coefficent of bird risk due to weather conditions senario
- DS_i is the distance of delivery point i to the sea

It is thought that as it get closer to the seaside, the bird density increases, therefore also the risk value icreases.

Finally, to calculate the bird risk rate between two points the equation below is preffered:

$$RBij = \frac{RBi + RBj}{2} . Dij \qquad [6]$$

Where:

- *RBij* represents the bird risk value between point i and point j
- *Dij* is the distance between point i and point j

To calculate environmental risk on drone durability, the following equation is used:

$$REij = C_2 . Dij \qquad [7]$$

Where:

- $REij$ represents the environmental risk on drone due to the weather conditions
- C_2 is the coefficent of environmental risk due to weather conditions senario

Finally, the total risk value between two points i and j can be calculated by using the following equation:

$$Rij = RBij + REij \qquad [8]$$

After calculating the distances of the buildings to the sea, bird risk and environmental risk on the drone are calculated with the formula above (Equation 8). Then, a risk matrix was created with the *Rij* values found.

In order to make an assessment of the risk level corresponding to the given risk values and the total risk rate of the resulting route, the study conducted by Başak and Gülen in 2007 was taken as basis. In this study, Başak and Gülen (2007) interviewed 30 military personnel who are sophisticated on UAVs and have past experiences about risks of drones were utilized by using with one-on-one interview method. The comprehensive list obtained as a result of the interviews was simplified and a basic list of 24 items was created to be used in practice. It was designed in such a way that each risk factor could receive a risk score between 1 and 5, and accordingly, it was stated that the total risk score would take a value of minimum 24 and maximum 120. In the risk assessment table created, 4 ranges were determined and risk scores between 24-48 were rated as negligible, 48-72 as important, 72-96 as critical and 96-120 as disaster. In order to determine the maximum acceptable risk limit in the problem applied within the scope of this thesis, the risk scale designed in above study has been taken into consideration. After calculating bird and drone durability risks, 4 equal intervals were created according to the lowest and highest risk and the maximum risk level was selected at the lowest limit of the level corresponding to critical.

The problem created was coded in Python software language and aimed to be solved with the artificial bee colony algorithm improved by harmony search algorithm and 2-opt search algorithm. Employed, onlooker and scout bee steps of the bee colony algorithm have been implemented in the code to solve drone routing while harmony search is applied for ABC parameter optimization and the 2-opt algorithm was used to improve the neighboor solution search during ABC procedure. The distance and risk values of the nodes in the problem were added to the code with the created distance matrix and risk matrix of the nodes. Distance and risk values are normalized by using Min-Max Normalization to bring in same scale, in order to make accurate calculations. In this way, scale differences were prevented from affecting the results. The results found with HABC-2O were compared with the results of another well-known swarm intelligence algorithm, the Ant Colony Algorithm (ACO) and classical ABC.

3.4. Mathematical Representation of the Risk Based Routing Problem

The developed mathematical model for the proposed drone delivery routing problem with risk and its constraints are represented in Figure 3.6. The objective function of the model (Eq. [9] in Figure 3.6) is to minimize the risk level that the UAV exposed to along its route while minimizing the total travel distance.

	Parameters
n:	Total number of nodes to visit (including the starting node)
$\mathbf{d_{ij}}$:	Distance between node i and node j
$\mathbf{r_{ij}}$:	Level of Risk Exposure between node i and node j
Rmax:	Maximum Level of Total Risk Exposure during the route
C:	Maximum distance that UAV can travel
	Variables
$\boldsymbol{X_{ij}}$:	Decision variable which is indicating if UAV is moving from point i to point j (It can be 0 or 1)
$\boldsymbol{U_i}$:	Auxiliary variable which indicates the order of visiting node i (It should be $\boldsymbol{U_1} = 1$ and $2 \leq \boldsymbol{U_j} \leq \boldsymbol{n}$)
	Objective Function
	Minimize $Z = \sum_{i=1}^{n} \sum_{j=1}^{n} [\, \boldsymbol{d_{ij}} \; +. \boldsymbol{r_{ij}}] \,. \boldsymbol{X_{ij}}$ [9]
	Constraints
	$\sum_{j=1, j \neq i}^{n} \boldsymbol{X_{ij}} \; = \; \mathbf{1} \quad \forall \boldsymbol{i} = \mathbf{1}, \mathbf{2} \ldots, \boldsymbol{n}$ [10]
	$\sum_{i=1, i \neq j}^{n} \boldsymbol{X_{ij}} \; = \; \mathbf{1} \quad \forall \boldsymbol{j} = \mathbf{1}, \mathbf{2} \ldots, \boldsymbol{n}$ [11]
	$\boldsymbol{U_i} \; - \boldsymbol{U_j} + \text{n} \,. \boldsymbol{X_{ij}} \leq \text{n} - 1 \quad \forall \boldsymbol{i}, \boldsymbol{j} = \mathbf{1}, \mathbf{2} \ldots, \boldsymbol{n}$ [12]
	$\sum_{i=1}^{n} \sum_{j=1}^{n} \boldsymbol{r_{ij}} \,. \, \boldsymbol{X_{ij}} \quad \leq \; \boldsymbol{Rmax}$ [13]
	$\sum_{i=1}^{n} \sum_{j=1}^{n} \boldsymbol{d_{ij}} \,. \quad \boldsymbol{X_{ij}} \quad \leq \; \boldsymbol{C}$ [14]

Figure 3.6. Mathematical Modelling of The Risk Based Routing Problem

The first constraint [10] and the second constraint [11] is created to ensure that each point on the route is visited only once and exited only once, respectively. The constraint [12] is added to eliminate subtours by using Miller-Tucker-Zemlin (MTZ) subtour elimination. The constraint [13] is defined to create a limit so that the total risk level does not exceed the specified maximum risk level. Besides, considering that the UAV has a limited flight distance, the constraint [14] is added so that UAV can visit all points within its range capacity.

This mathematical formula aims to minimize the total risk exposure level of UAV and total flight distance while also achieving defined constraints such as maximum risk level and maximum distance that UAV can travel.

3.5. Steps of ABC Algorithm Implementation for the Risk-based UAV Routing Problem

In the beginning of ABC algorithm, a random route is generated and set as the best route to start with. In the algorithm, an abandonment limit is kept for each solution. When the specified maximum limit is reached, it means that the solution will be abandoned. It is understood that this solution is not good enough and new solutions are searched. The abandonment counter helps to ensure the balance of exploration and exploitation of the algorithm. The subscription counter for the random route created at the beginning of the algorithm is initialized with 0. The initial route is evaluated for compliance with the maximum risk and distance constraints; if not, a new random route is created and the same checks are repeated. If a route complies with the constraints, algorithm is continued. According to these, the basic code of the ABC algorithm in the proposed model can be expressed as in Figure 3.9.

Until the maximum iteration number is reached; a new route is created by randomly changing 2 points from the current route and the objective value is calculated and compared with the current route. If the current route has a better objective value than the new route, the current route is continued and the abandonment counter is increased by 1. The current route continues to be accepted as the best route and the algorithm is run over the current route again for the next iteration. In this case, if the AC value reaches the predetermined abandonment limit (AL), this route is completely abandoned and a new random route is created by going back to the beginning.

1.Initalization

1.1. Determine the initial position of UAV

1.2. Generate an initial route randomly

1.3. Set best route and best distance to the initial route and distance

1.4. Set Abandonment Counter (AC) to zero and specify the Abandonment Limit (AL) value

1.5. Check the initial route's risk level and travel distance constraints

1.6. If maximum risk level or travel distance of the initial route exceed the limits, turn back to step 1.2. and generate a new initial route

2. Running the Algorithm

2.1. Repeat for the specified maximum number of iterations

2.1.1. Generate a new solution (route) from the current solution

2.1.1.1. Select two nodes from current route randomly and create a new route by changing the position of selected nodes

2.1.2. Calculate the objective function to evaluate the new route

2.1.2.1. Calculate the total distance and risk level of the new route

2.1.2.2. Calculate the objective function

2.1.3. If the new route is better than current route;

2.1.3.1. If maximum risk level or maximum distance of the new route exceed the limits, turn back to step 2.1.1. and generate a new route. If it does not exceed, continue

2.1.3.2. Update the best route and best distance according to new route

2.1.3.3. Reset AC = 0

2.1.4. If the current route is better than new route, continue with current route

2.1.4.1. Increase AC value by 1.

2.1.5. If AC value reaches the AL value;

2.1.5.1. Turn back to step 1.2. to generate a random new route

3. Return the best solution and exit.

Figure 3.7. Basic Steps of ABC Algorithm for The Risk-Based Drone Routing

If the new route has a better objective value than the current route, its compliance with the risk and distance restrictions is checked. If it does not exceed the limits, the best route is updated with this new route and the abandonment counter is reset. If it exceeds the limits, another 'neighbor' route is created from the current route and the same checks are repeated. In this way, when all iterations are completed, the best route and distance and risk values are presented as the algorithm output.

ABC algorithm was used in the solution of the problem. 2-opt algorithm was used for the neighboring solutions created during the search of neighboring solutions of the algorithm to enhance the algorithm performance. With 2-opt algorithm, a new neighboring tour is created by swapping two edges of the tour, that is, by changing the order between 2 points. 2-Opt algorithm is one of the effective methods in the optimization of tours by performing local search. Harmony search optimization algorithm was used to provide parameter optimization in the bee colony algorithm. Exploration is the ability to find different combinations of parameters, whereas exploitation is the use of the best solutions found so far, and Harmony Search is capable of doing both. Reaching such a balanced state permits one to achieve better overall performance. This implementation is referred to as 2-Opt Harmony Based Artificial Bee Colony (HABC-2O) Algorithm.

3.6. 2-Opt Harmony Based Artificial Bee Colony (HABC-2O)

Harmony search algorithm is one of the meta-heuristic algorithms and based on music and notes (Askarzadeh and Rashedi, 2017). It is based on the concept of musical harmony and was developed to simulate that solutions can be found within a certain 'harmony'. In music, perfect harmony is sought with certain sound and note combinations; musicians strive to ensure that the notes come together in the best way possible and meet the criteria of taste. Musicians search for general appreciation and memorize sounds that are appropriate for their purpose.

There are 3 possibilities for musicians: playing an existing track from memory, playing a known track from memory with a slight modification, or creating a completely new track. Based on this, musicians' search for the best harmony inspired the creation of an optimization algorithm. Geem et al. (2001) applied this behavior of musicians as a searching algorithm. The most important feature that distinguishes the Harmony search algorithm from other metaheuristic algorithms is that the new solution is selected among the entire existing population. Additionally, it combines both heuristic and random search techniques (Askarzadeh and Rashedi, 2017). The main parameters of the algorithm include the harmony memory size (HMS) and the usage rate of this memory (HMCR), the number of iterations, and the tone adjustment ratio (PAR). HMS specifies how many of the solutions will be kept in harmony memory. HMCR expresses possibility of using the solutions from memory to create new solutions. PAR is used to decide whether the solution in memory can be changed to a neighboring solution or not when harmony memory is decided to be used in the process of generating a new solution. The flowchart of Harmony Search algorithms is given in Figure 3.8 (Lakshmi & Rao, 2018).

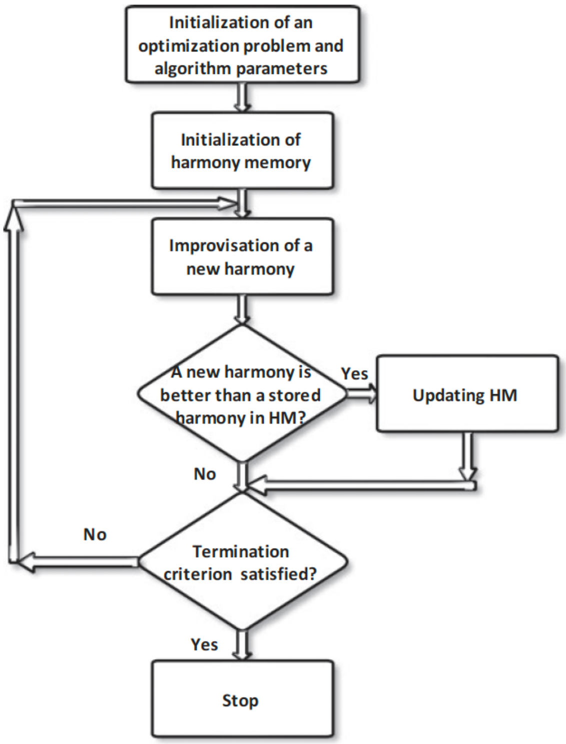

Figure 3.8. Basic Flow of Harmony Search Algorithm

Initially generated random solutions are stored in the harmony memory. To generate a new solution, a random solution is selected from memory, and a new solution is derived from this solution. The new solution obtained is compared with other solutions in the memory. A better solution is replaced with the solutions in memory and added to memory. When memory is full, the worst solution in memory is removed and a new solution is added instead of it. These steps are repeated for the specified number of iterations. When iterations are completed, the best solution in memory is presented as the result.

By combining ABC algorithm with harmony search, a more effective method has been created in parameter determination. Good parameter combinations are kept in harmony memory and better parameters are estimated based on the parameters in this memory.

For HABC-2O, the flow can be defined as follows:

- Define the algorithm parameters randomly between predetermined ranges
- Create a harmony memory to store parameters and best solutions
- Start the loop of harmony search
    - Select parameters randomly and add initial solutions to harmony memory
    - Run the ABC Algorithm
        - Create initial population randomly (random tours)
        - Assign the roles for bees as employed or onlooker bee
        - Employed Bee Phase
            - Local search on the assigned tours,
            - Create neighboor solutions with 2-Opt and try to improve the solution
        - Onlooker Bee Phase
            - Investigate the fitness values of solutions found by employed bees
            - Compare the fitness values and select the best solutions
            - Explore new solutions based on evaluation of fitness values
        - Scout Bee Phase
            - If current solution cannot be improved for a certain limit, replace that solution with the new random solution
        - Memorize the best solution found during ABC iteration.
    - If best solution found during ABC is better than the worse solution in the harmony memory, update the harmony memory with new best solution and its parameter combination and delete the worst solution from the memory.
    - For new iteration, predict new parameters based on harmony memory storage until all iterations are done.
        - Create a random number between 0-1.

- If random number is smaller or equal to HMCR, choose a solution from harmony memory.
    - Create a random number between 0-1.
        - If random number is smaller or equal to PAR, change each parameter of the solution slightly.
        - Otherwise, do not change the solution.
- Otherwise, create a new random solution

- Print the best solution and corresponding parameters and finish the algorithm.

In addition, in the neighboring solution generation of ABC algorithm, 2-opt local search is used to reverse the sub-tours between the selected 2 points and neighboring tours are found. In this way, instead of changing the place of 2 points in the tour as in classical ABC, a better diversified neighboring tour has been found. 2-opt is a local optimization algorithm for the TSP problems found by Croes in 1958; which try to reduce overall distance of the tour by reversing two random edges from that route (Keskintürk et al., 2016). An example representation is given in Figure 3.9 (Djordjevic et al., 2009) to show how 2-Opt changes the nodes.

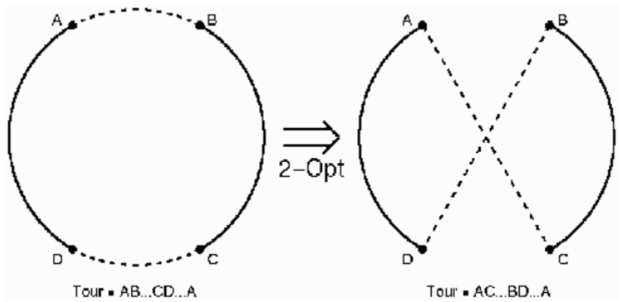

Figure 3.9. Example for Exhange of Nodes in 2-Opt Algorithm

2-opt local search was used to increase the solution quality and prevent getting stuck in local minimum of the ABC algorithm during the new neighboor solution selection processes.

4. RESULTS AND DISCUSSIONS

In this study, a pilot region was selected for multiple package delivery using a single drone. Bird risk and environmental risks that may affect drones in this region were calculated. HABC-2O algorithm was used to find the optimal route that minimizes distance and risk in the selected pilot region. The results were compared with ACO, another well-known swarm intelligence algorithm frequently used in TSP applications. In order to perform parameter optimization of the ACO algorithm, the experimental analysis method was used and 100 experimental scenarios within the specified ranges of parameters were created. The Random Search method was applied on a created dataset. In the experiments, parameters have a uniform random value within the specified ranges, and each experiment was tested for a certain number of trials which is 50. After, the result set obtained for each experiment was evaluated and the parameter combination that could find the most consistent results was preferred. After parameter optimization for ACO, both ACO and the proposed model HABC-2O were run on the problem and the results were compared. In order to compare the success of the proposed algorithm, a solution was also made with the classical ABC algorithm.

4.1. Experimental Design for Parameter Optimization of ABC and ACO

In order to perform parameter optimization of the ACO algorithm and classical ABC algorithm, the Experimental Design approach was used, and 100 experiments were created. Uniform random parameter values were created so that each experiment had a different parameter combination by simple random sampling. The algorithm parameters for ACO are the number of ants, number of iterations, pheromone evaporation rate, influence of pheromone and influence of heuristic taken into consideration. The number of ants parameter took integer values between 2 and 50. The number of iterations was determined to be between 50 and 300. Other parameters in the ACO algorithm; pheromone evaporation rate to take a fractional value between 0 and 1; influence of pheromone and influence of heuristic are designed to take fractional values between 0.5 and 5. While determining the value range of evaporation rate, pheromone effect and heuristic effect, the general trend in the literature was taken as basis. Parameter values distributed uniform randomly in specified ranges are given in Appendix B.

For the classical ABC application, 100 experimental scenarios were created; the number of bees was given between 2-50, and the number of iterations was between 50 and 100. The lower limit for the limit value was determined as 10 and the upper limit as the number of iterations. The reason for this is that if the abandonment limit is higher than the number of iterations, it contradicts the logic of the algorithm. Undeveloped solutions are abandoned when they reach a certain limit. If this limit is given greater than the number of iterations, it is possible to get stuck in an undeveloped solution and a situation separate from the logic of the algorithm occurs.

For 100 experiments, each experiment was run 50 times, and the results were recorded. The Coefficient of Variation (CV) method was used to determine the most consistent combination of parameters. It is also called relative standard deviation (RSD). When RSD score multiplied by 100, it is called Coefficent of Variation. CV is frequently used in statistics to express the distribution of a group of data around the group mean. It is found by dividing the standard deviation value of the data group by the average value. It is used to express the distribution of data around their centers. A high CV value indicates that the data are distributed further from the mean. Therefore, it indicates that the deviations from the average and the risk are large. A smaller CV value is more reliable as it indicates a more consistent data set. CV was preferred to compare the experimental results made with the random search method. The CV value was calculated by finding the standard deviation and average of the objective function values obtained as a result of running each experiment 50 times. Then, it was accepted that the experiment with the lowest CV value was the hyperparameter combination that led to the most consistent results. CV calculation can be shown with following equation [15]:

$$\mathrm{CV} = \frac{Standart\ Deviation}{Mean}\ x\ 100 \qquad [15]$$

As a result of the calculations; the best, which means the lowest, CV value for classical ABC algorithm is found as 0,778. Correspondingly, the most consistent experiment is

37th experiment. For ACO, after the calculations, the lowest CV value is found as 0.427 and corresponding experiment is 95th experiment. This experiment has the parameter values as number of ants=41, iteration number=185, evaporation rate=0.6, influence of pheremone=0.5 and influence of heuristic=4.4. When the most optimal parameter combination of ACO is examined, it is seen that the influence of pheremone is closer to the lower bound and the influence of heuristic is positioned close to the upper bound. At this point, it can be inferred that when the pheromone effect is low and the heuristic effect is high, the algorithm tends to explore rather than exploit, which is reflected positively in the results.

Additionally, for some parameter combinations, ACO could not find the optimum result in some of the 50 trials. A total of 500 results were collected for both algorithms with 100 experiments and 50 trials, and ABC was able to find a result with 100% success in 500 results. ACO's success in finding a result varied according to the parameter combination and could not find a valid tour in 123 out of 500 results, and the success rate was 75.4%. This shows that while ABC can provide a result, although not optimal, independently of the parameter combination; ACO's ability to find a result depends more on the parameter combination. In ACO, parameter setting combination have a much greater effect on the quality of the result. In this case, we can conclude that ABC has a flexible and general analysis ability; ACO is less flexible but can achieve better results when optimized for certain situations.

4.2. Performance Comparison of HABC-2O, ABC and ACO Algorithms on the Proposed Problem

In this section, the results of the proposed model HABC-2O, ABC and ACO algorithms with the determined parameters for the proposed problem are compared. Additionally, in the problem constraints, the maximum flight distance for the drone was determined as 30 km. Another constraint, the maximum risk constraint that the route can have, is determined as 341 according to the risk assessment scale model taken as an example. All algorithms were run 30 times on the problem by using parameters determined in the previous section. The best scores obtained after 30 runs were recorded.

In order to calculate the risk score in the selected region, risk calculations were made assuming that the weather was warm and moderately windy in the created scenario. The total risk score that the route that is formed in our problem can take values between 112 and 550. Therefore, the maximum acceptable risk level has been determined as 341; which is correspond to the starting value of the 'critical' level, which is ranges given in the above study. In other words, the aim is to ensure that the risk score of the route to be determined for drone routing is below the critical level. The algorithms were run by applying the specified distance and risk constraints after the distance matrix and risk matrix were created.

The results of the algorithms used to solve the proposed UAV routing problem are given in Table 4.1. It shows the best distance in km, total risk scores and objective values of the tour that HABC-2O, ABC and ACO algorithms can find.

Algorithm	Total Distance (km)	Total Risk	Objective Value
HABC-2O	11,26	240,29	8,735
ABC	11,81	253,72	9,193
ACO	11,32	241,33	8,779

Table 4.1. Comparison of Algorithms' Results

Moreover, the bar chart representation of the comparison is given in Figure 4.21 As it can be seen, the proposed algorithm provided a better risk score than the classical ABC and ACO and was able to find the least risky route. While the classical ABC was far from the best value; ACO could approach but could not reach the minimization as good as the proposed algorithm. The total distance values are close to each other, but the proposed algorithm was able to achieve a much better result than the others. The fact that the total distance values are closer may be due to the narrowness of the selected area in the solved problem. However, although the differences are small, it is seen that the proposed algorithm provides better minimization.

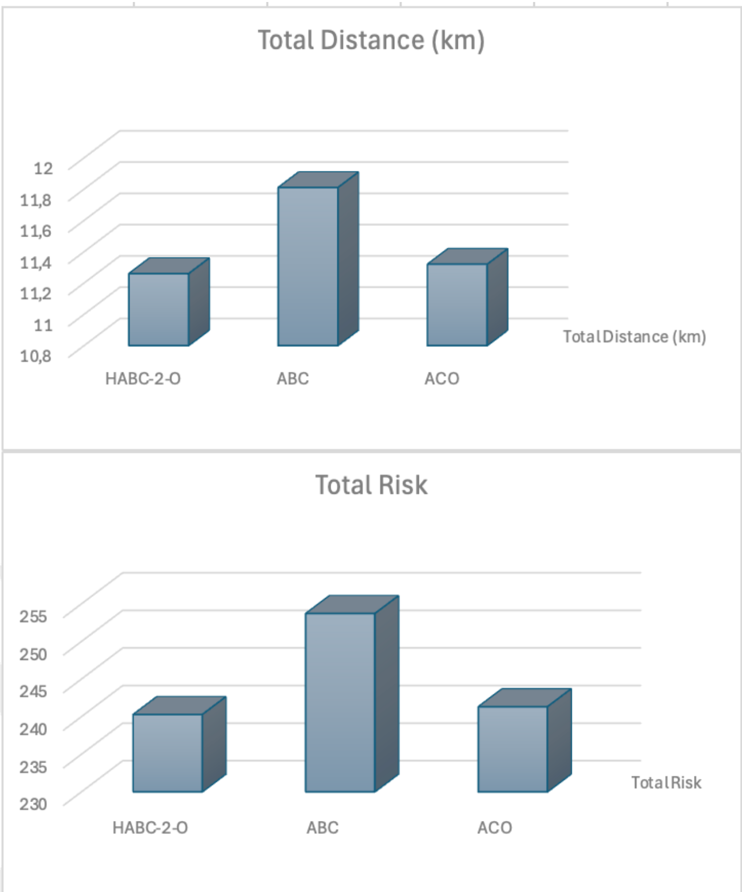

Figure 4.1. Bar Chart Comparison of Results

In addition, the algorithms were run on the problem 30 times in succession and the best results were selected. In the classical ABC, it found its best result only once in 30 runs, and the other 29 results were worse. ACO, on the other hand, was able to reach the best result 3 times in 30 runs. The proposed HABC-2O algorithm found the same better result in 19 times over 30 trials. This shows that the proposed model has a higher probability of finding the optimum result in fewer trials. In Figures 4.2, 4.3 and 4.4, the best route found by HACBC-2O, ABC and ACO is drawn and shown, respectively.

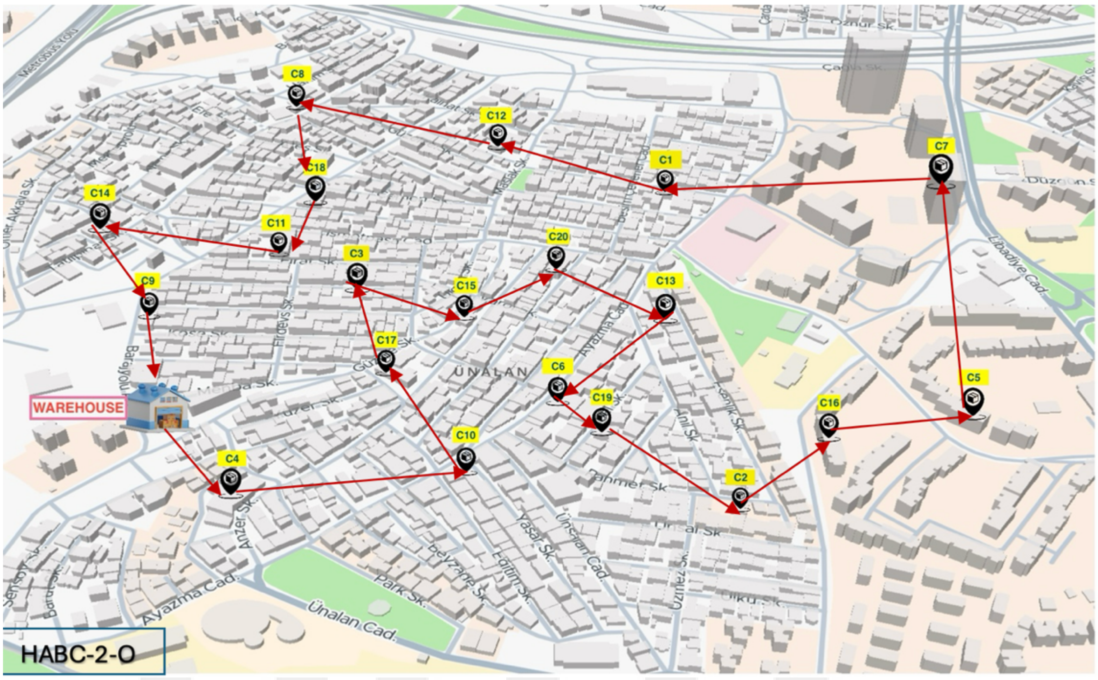

Figure 4.2. Best Route for HABC-2O

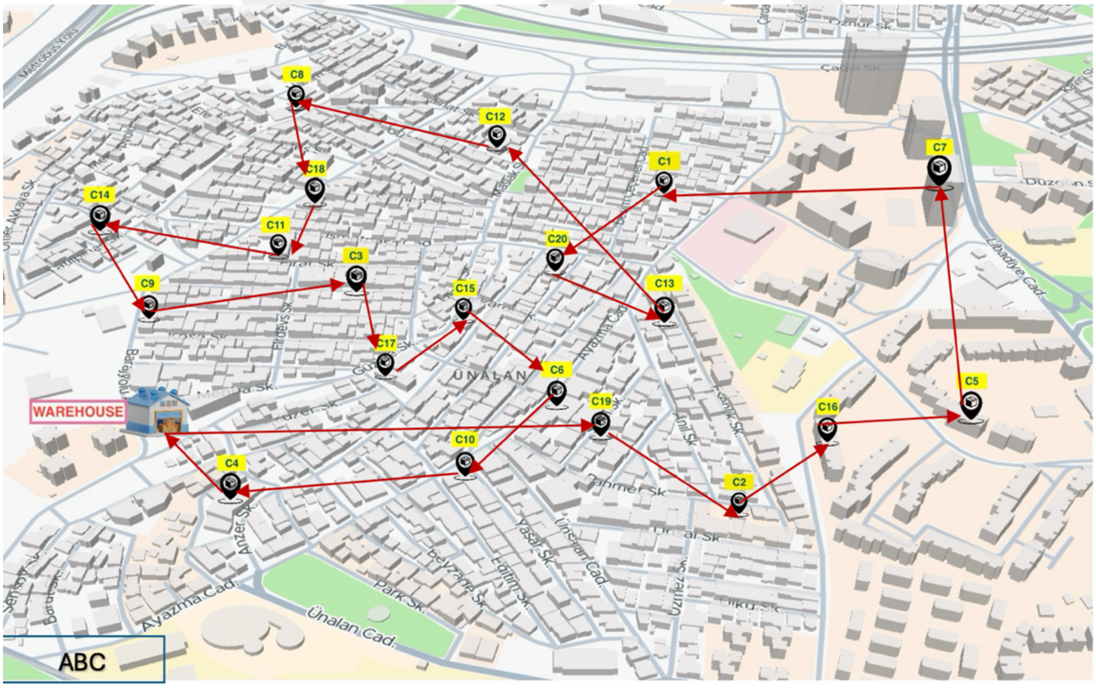

Figure 4.3. Best Route for ABC

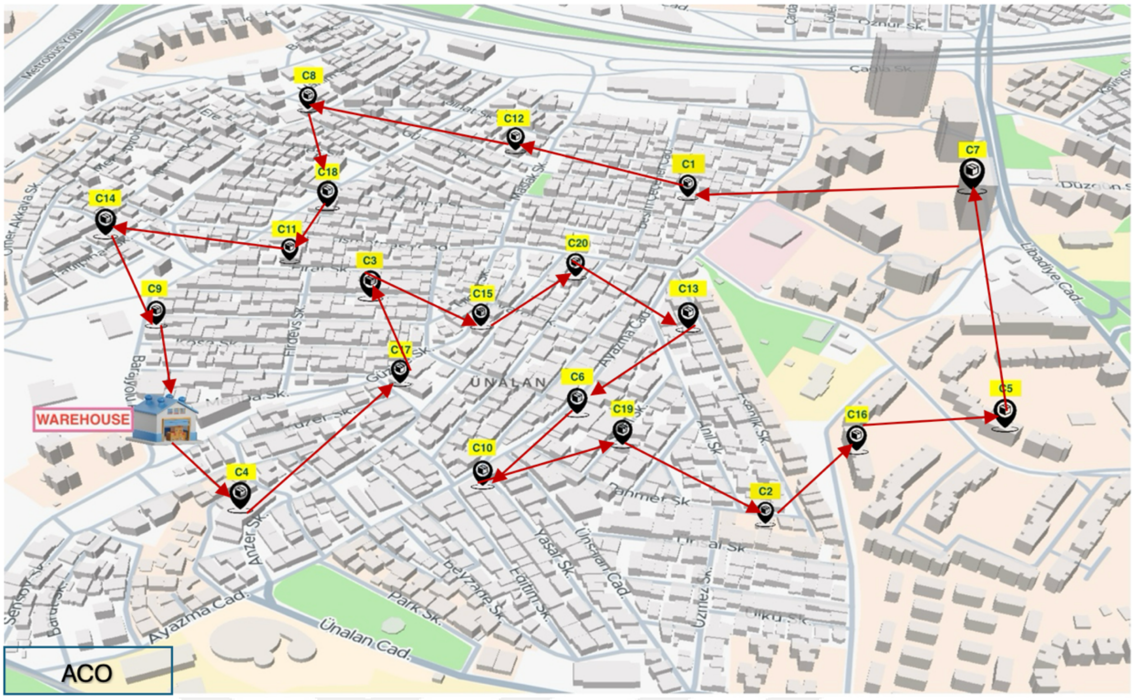

Figure 4.4. Best Route for ACO

Moreover, also the proposed algorithm model is solved on Berlin52, a well-known TSP problem in the literature. It was compared with the results of other algorithms on the same problem and it was seen that it gave better results. The HABC-2O algorithm found 7544.365 as the best optimum result for the Berlin52 problem. When the algorithm results in the studies (Hossain & Acar, 2024; Altıok & Koçer, 2015) are examined, it has been seen that it gives better results than many metaheuristic algorithms such as ABC, ACO, GA. In this way, it has been revealed that the proposed algorithm gives more successful results not only for the problem defined within the scope of this study, but also for generally accepted TSP problems. Thus, the effectiveness and general validity of the algorithm against different types of problems have been demonstrated.

Overall, the use of the HABC-2O algorithm in drone delivery routing studies, especially when the risk factor is taken into consideration, stands out as a preferable algorithm in terms of both minimizing the risk and distance. At this point, it can be said that the HABC-2O algorithm has a more sophisticated approach than classical ABC and ACO algorithms. While HABC-2O provides a more effective neighborhood solution generation with the 2-opt algorithm, parameter optimization with harmony search prevented the algorithm from getting stuck locally and improved the results considerably compared to classical ABC, bringing it closer to the global optima. HABC-2O has modified the classical ABC algorithm to give better results compared to ACO, which is another algorithm frequently used in TSP problems.

5. CONCLUSION

As of today, drone technology stands out as one of the disruptive tools for enhancing logistics and shipping operations. Many large retail or cargo companies around the world are working on drone deliveries and incorporating drones into their operational processes. Drones can provide reliable and fast deliveries even to locations where the transportation system is not sufficiently developed or are difficult to reach due to environmental factors. However, in addition to the benefits offered by drone routing, there are also threats that need to be addressed, such as environmental factors or technical reasons. When the risks that may be encountered in drone use and routing processes are correctly assessed, the future directions of the technologies developed in particular, the cities of the future and the logistics processes can be improved in a sustainable way. Especially, the ability of swarm intelligence algorithms in this process takes the decision-making process to another scale by making it possible to have adaptive systems that work efficiently in unstable conditions. Particularly, the integration of swarm intelligence applications into drone technology has enabled great steps to be taken in achieving better results and ensuring the autonomy of drones. In this way, the time and the resources are used more efficiently. In this study, the effect of the use of swarm intelligence algorithms on drone shipment problems was evaluated.

First, a pilot area to be delivered was determined and 20 customer points were randomly selected in this area. After determining the coordinate information of the delivery points, the distances between the warehouse and delivery points were calculated. A solution was made on the proposed model, 2-Opt Harmony Based Artificial Bee Colony (HABC-2O). The results were compared with the classical Artificial Bee Colony Algorithm and Ant Colony Algorithm, which are swarm intelligence algorithms. The algorithms are coded using Python Software. For the results, firstly, Random Search was applied to find the best combination of parameters for ABC and ACO. Then, distance and risk values were determined by determining risk scores on the selected pilot region. Solutions were calculated 30 times for all 3 algorithms and the best results were compared. It was seen that 2-Opt Harmony Based Artificial Bee Colony (HABC-2O) found a better tour and better distance and risk values compared with other 2 algorithms. Although multiple package distribution studies with a single drone are not yet applicable in real life, it is thought that with advancing technology and increasing needs, real life applications will begin in this area. Especially in such delivery applications, optimization of the problem, operational convenience, speed and operational safety are very substantial.

For future work, recharging points can be added to the single drone usage for multi-package deliveries in the proposed model, so that possibility of delivering to larger areas and more customers with a single flight of the drone may be examined.

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APPENDIX A. Parameter Settings of Experiments for ABC Algorithm

Experiment No	Number of Bees	Number of Iterations	Abondenment Limit
1	36	246	111
2	9	188	129
3	25	157	67
4	40	59	54
5	39	133	97
6	39	292	160
7	27	245	52
8	29	171	23
9	19	291	246
10	15	227	45
11	12	265	160
12	13	272	228
13	18	77	32
14	25	69	50
15	2	231	114
16	33	289	12
17	29	139	82
18	34	169	128
19	39	216	24
20	30	152	140
21	29	59	38
22	46	140	138
23	3	268	252
24	21	188	24
25	40	71	69
26	7	150	138
27	33	99	89
28	18	82	78
29	30	295	12
30	50	165	28
31	40	92	72
32	33	75	53
33	9	183	56
34	8	241	26
35	32	99	94
36	48	293	109
37	43	266	94
38	34	277	116

Experiment No	Number of Bees	Number of Iterations	Abondenment Limit
39	17	120	68
40	25	243	172
41	32	214	144
42	9	81	64
43	8	259	221
44	39	174	131
45	17	231	117
46	18	209	53
47	37	95	61
48	8	97	41
49	35	265	187
50	31	256	137
51	34	281	207
52	30	98	82
53	13	217	100
54	28	176	134
55	31	268	25
56	11	195	172
57	33	246	66
58	18	217	53
59	29	215	110
60	15	188	26
61	41	67	14
62	49	168	94
63	21	271	192
64	49	262	109
65	15	55	29
66	45	107	48
67	44	142	87
68	41	128	79
69	5	102	36
70	22	125	22
71	30	274	256
72	47	58	15
73	24	196	54
74	4	138	36
75	19	77	55
76	6	247	235
77	9	157	100
78	24	91	11
79	25	287	77

Experiment No	Number of Bees	Number of Iterations	Abondenment Limit
80	32	246	236
81	42	296	92
82	19	259	91
83	11	66	64
84	27	54	54
85	50	234	167
86	28	238	61
87	14	262	207
88	38	50	23
89	38	206	96
90	31	268	170
91	44	240	66
92	3	300	253
93	8	99	13
94	3	290	208
95	50	242	18
96	38	259	153
97	20	99	51
98	36	96	92
99	17	171	68
100	43	261	104

APPENDIX B. Parameter Settings of Experiments for ACO Algorithm

Experiment No	Number of Ants	Number of Iterations	ρ	α	β
1	34	205	0,4	1,1	1,2
2	3	233	1	3,1	0,9
3	32	219	0,1	2,2	5
4	7	163	0,5	2,8	0,9
5	12	293	0,4	2,4	0,6
6	19	267	0,7	2,6	1,6
7	44	232	0,1	2,3	4,6
8	25	250	0,5	4,5	3,8
9	24	158	0,7	4,5	1,9
10	27	53	0,1	4,2	1,2
11	35	245	0,9	1	0,5
12	7	206	1	4,4	0,5
13	31	289	0,3	4,7	2
14	27	182	0,9	2,9	3,7
15	39	155	0,9	3,5	1,5
16	33	54	0,8	1,6	2,3
17	37	71	0,2	2,6	2,4
18	35	80	0,1	3,5	1,9
19	14	188	0,9	1,2	3,1
20	28	290	0,4	2,3	2,2
21	47	144	0,1	2,4	0,8
22	14	223	0,8	1,9	2,4
23	41	173	0,6	2,1	4,4
24	20	253	0,3	1,2	1,8
25	7	102	0,9	3,1	3,3
26	21	89	0,8	4,7	2,7
27	35	155	0,4	4,9	0,7
28	41	254	0,3	0,6	4,7
29	22	295	0,5	0,9	0,8
30	25	163	0,2	2,9	4,1
31	11	65	0,5	4,2	1,4
32	35	75	0,1	3,7	0,7
33	23	249	1	2	1,6
34	3	122	0,2	0,7	0,9
35	9	55	0,8	2,9	2,4
36	35	157	0,5	0,8	1,9
37	31	280	0,4	4,6	3
38	9	238	0,8	1,5	1,5

Experiment No	Number of Ants	Number of Iterations	ρ	α	β
39	17	170	0,3	4,7	2,5
40	13	61	0,7	2,9	2
41	22	147	0,5	3,7	4,1
42	30	243	0,9	2,1	3,8
43	19	155	0,9	0,5	1,2
44	40	264	0,1	3,9	4,2
45	47	79	0,9	1,5	3,8
46	26	206	0,5	2,7	4
47	11	275	0,2	4,5	2,2
48	10	120	0,6	2,5	5
49	23	232	0,8	3,2	2,7
50	3	197	1	4,6	1,8
51	14	285	0,3	5	3,1
52	6	165	1	3,8	0,8
53	12	289	0,9	5	3,3
54	16	274	0,1	1,2	3,2
55	20	59	0,9	4,1	3,3
56	14	202	1	1,1	2,7
57	4	239	0,3	4,8	4,5
58	34	229	0,3	4,9	0,6
59	19	70	1	3,3	2,2
60	23	141	0,3	4,4	2,9
61	12	68	0,3	1,1	0,5
62	15	116	0,5	4	2,2
63	27	52	0,7	4,2	2,3
64	30	199	0,9	0,8	2,4
65	11	213	1	4,9	4,1
66	27	141	0,6	2,2	4,3
67	41	59	0,1	4	1,6
68	10	284	1	2,7	2,9
69	34	131	0,9	2,9	0,7
70	41	71	0,5	4,8	2,9
71	25	106	1	2,7	0,6
72	35	97	0,3	4,4	2,9
73	20	245	0,4	3,6	1,3
74	36	84	1	2,5	3,7
75	27	119	0,2	4,9	1,5
76	31	111	1	1,5	4,7
77	49	90	0,5	2,1	1,9
78	30	175	0,1	3,5	4,7
79	43	166	0,9	4,1	2,3

Experiment No	Number of Ants	Number of Iterations	ρ	α	β
80	17	274	0,4	3,1	1,5
81	11	53	0,8	3,1	0,6
82	16	93	0,4	4	3,3
83	46	277	0,2	1,3	4,2
84	21	249	0,6	2,2	2,7
85	13	300	0,5	0,8	3,4
86	11	56	0,9	2,9	1,4
87	49	115	0,6	2,8	0,7
88	26	257	0,1	2,6	2,1
89	14	278	0,1	3	1,8
90	10	253	0,1	2,1	3,6
91	44	66	0,4	1,9	2,6
92	17	129	0,9	3,3	4,5
93	30	100	0,1	3,7	1,4
94	47	263	0,2	1,9	2,7
95	41	185	0,6	0,5	4,4
96	25	186	0,6	4,4	3,3
97	27	249	0,8	2,8	1,3
98	8	117	0,9	4,4	3,1
99	21	290	1	3,6	5
100	23	262	0,3	3,1	0,8

BIOGRAPHY

Ezgi Kayış holds Bachelors degree in Industrial Engineering. She was graduated from the faculty with honor degree. She has been working in the field of cryptology and electronic data security as a Senior Researcher at the National Scientific and Research Institution for more than 3 years. Her main research interests include Swarm Intelligence, Artificial Intelligence and Machine Learning, optimization of vehicle routing and drone technologies.