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Mathematical Optimization in Innovation Productivity: A Framework and A Case Study on UAV Border Patrolling in Türkiye

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ABSTRACT

Purpose: In this paper, the potential of mathematical optimization (MO) in enhancing innovation productivity is explored. Innovation is a process that converts new ideas and methods into products and services, MO can contribute to innovation management by improving productivity across all stages, from pre-innovation to post-innovation. This paper establishes a connection between MO and innovation productivity while demonstrating an application for a post-innovation phase problem of unmanned aerial vehicles (UAVs).

Methodology: A framework for incorporating MO into the design problems of innovation processes is developed. Additionally, a MO model is developed for a case study concerning UAV border patrolling in Türkiye.

Findings: Computational experiments demonstrate MO's effectiveness in optimizing UAV routes and strategies, enhancing operational efficiency, and innovation productivity. Optimal recommendations and trade-offs among different mission considerations are obtained in 18 minutes on average (with a median of 5 seconds) over 210 runs.

Originality: A link is established between MO and innovation productivity. An operations research problem is introduced for UAV operations in border patrolling in Türkiye. The codebase and data are openly provided for readers to apply the model in their research.

Keywords: Mathematical Optimization, Innovation, Productivity, Unmanned Aerial Vehicles.

JEL Codes: C60, C61, C63, O32.

İnovasyon Verimliliğinde Matematiksel Optimizasyon: Bir Çerçeve ve Türkiye'de İHA Sınır Devriyesine İlişkin Bir Vaka Çalışması

ÖZET

Amaç: Bu makalede, matematiksel optimizasyonun (MO) inovasyon verimliliğini artırma potansiyeli incelenmektedir. İnavasyon, yeni fikirleri ve yöntemleri ürün ve hizmetlere dönüştüren bir süreçtir. MO, inovasyon yönetimine verimliliği artırarak katkıda bulunabilir; bu, inovasyon öncesinden sonrasına kadar inovasyon sürecinin tüm aşamalarında geçerlidir. Bu makale, MO ve inovasyon verimliliği arasında bir bağlantı kurarken, insansız hava araçlarının (İHA'ların) inovasyon sonrası aşamasındaki problemlerine yönelik bir uygulama sunmaktadır.

Yöntem: İnovasyon süreçlerindeki karar problemlerine MO'nun dahil edilişi için bir çerçeve oluşturulmaktadır. Ayrıca, Türkiye'deki İHA sınır devriyesi ile ilgili bir vaka çalışması için bir MO modeli geliştirilmektedir.

Bulgular: Hesaplamalı deneyler, MO'nun İHA rotalarını ve stratejilerini optimize etme, operasyonel verimliliği ve inovasyon verimliliğini artırma konusundaki etkinliğini göstermektedir. Model, optimal tavsiyeleri ve farklı endişeler için dengeleri 210 farklı çözüm için ortalama 18 dakikada (medyan 5) bulmaktadır.

Özgünlük: MO ve inovasyon verimliliği arasında bir bağlantı kurulmuştur. Türkiye'de sınır devriyesi için İHA operasyonları için bir yöneylem araştırması problemi sunulmaktadır. Okuyucuların araştırmalarında modeli uygulayabilmeleri için kod tabanı ve veriler açık sunulmaktadır.

Anahtar Kelimeler: Mathematical Optimization, Innovation, Productivity, Unmanned Aerial Vehicles Matematiksel Optimizasyon, İnovasyon, Verimlilik, İnsansız Hava Araçları.

JEL Kodları: C60, C61, C63, O32.

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1. INTRODUCTION

Innovation is a transformative process that converts novel ideas and methodologies into products and services. It ultimately contributes to the competitiveness of individuals, companies, societies, and economies. This process encompasses several key stages, including the discovery of new ideas, the conversion of ideas into tangible products and services, and the implementation in practice to generate added value for individuals, countries, and the planet.

Throughout the course of human history, innovations have played a pivotal role in driving transformative developments. In the past decade alone, significant changes have been witnessed. One noteworthy example is the advancements in Electric Vehicle (EV) technology, spearheaded by companies like TESLA, which are revolutionizing the automotive industry (Teece, 2018). Similarly, innovations in renewable energy technologies have yielded remarkable outcomes, such as the reduction in solar panel costs and the mitigation of energy supply continuity issues through advanced battery systems (Moustakas et al., 2020). Innovations in areas like blockchain technology, encompassing decentralization, persistence, anonymity, and auditability, are reshaping the realms of finance and supply chain management (Zheng et al., 2018).

Innovation plays a pivotal role in the advancement of countries, enabling the creation of new industries, boosting productivity, fostering sustainable growth, and driving economic development. Cantner et al. (2019) demonstrate the positive impact of public innovation incentives and innovations on long-term economic development in German regions. Similarly, Minford and Meenagh (2019) use a data-driven empirical modeling in the United Kingdom and show that research and development incentives stimulate economic growth. Consequently, governments prioritize and incentivize innovation in their policy-making strategies. Türkiye also recognizes the significance of innovation as a government strategy and policy and encourages innovations, evident in its investments in Unmanned Air Vehicles (UAV) and Electric Vehicles (EV).

Productivity, on the other hand, refers to the efficiency of transforming inputs into outputs. It quantifies the relationship between outputs and inputs, reflecting the output achieved per unit of input. There is a close and mutually reinforcing relationship between innovation and productivity. Innovation plays a vital role in enhancing the productivity and competitiveness of enterprises and economies. Conversely, productivity serves as a driving force for innovation, exerting its influence throughout every stage of its initiation, advancement, and implementation.

A typical innovation process involves numerous design problems. Enhancing productivity in these decisions is crucial. Traditional approaches rely on human intelligence and manual solutions. However, the scalability of human problem-solving is limited to small-sized problems. As decision problems have become increasingly complex due to larger data sizes and competitive environments, it has become imperative to integrate analytical approaches into the decision-making process. Fortunately, this is now more achievable in the context of the current digital transformation. Improved computational power and access to big data enable decision-makers to utilize analytical tools for their design problems. Analytical approaches have been recently popularized under the framework known as Artificial Intelligence (AI). AI overcome the limitations and scalability challenges faced by human intelligence, enabling them to process and analyze vast amounts of historical data more efficiently and make data-driven automated decisions. AI can identify new directions for innovation, optimize production costs, identify potential issues, and enhance efficiency and performance during implementation.

There exists an important field that falls under the AI umbrella: Mathematical Optimization (MO). MO is a specific implementation of Operations Research (OR). It formulates decision-making problems into mathematical models and solves them using theories like linear algebra. OR has a long-standing history, and MO emerges as a contemporary transformation of its methodologies, leveraging computational resources to solve optimization problems without the need for extensive theoretical frameworks for users. Solver technologies like Gurobi and CPLEX have achieved remarkable performance levels (Mittelmann, 2020) enabling automated solutions for complex problems through programming and software. Consequently, decision-makers have begun to leverage MO without requiring extensive expertise or a strong background in the field. MO can contribute to product, process, and method innovations, offering enhanced productivity performance. It can address problems of a scale that surpasses human intelligence throughout the entire innovation process, encompassing design problems of the pre-innovation, during innovation, and post-innovation stages. What sets MO apart, particularly from other predictive AI methods, is its capability to recommend decisions that are guaranteed to be optimal. This distinctive feature positions it in a unique and valuable role.

In this paper, the focus is on advancing the understanding of the potential of MO in enhancing innovation productivity. An empirical case study is then developed to demonstrate the application of MO in utilizing a UAV fleet for border patrolling in Türkiye. The contributions of the paper can be summarized as follows:

- A link is established between MO, artificial intelligence, and innovation productivity. A framework is presented for incorporating MO into design problems of innovation processes.
- A novel operations research problem is presented in the context of UAV operations for border patrolling in Türkiye. A mathematical formulation is developed, and computational experiments are conducted to explore its efficacy. By optimizing the UAV routes and strategies, MO not only improves the operational efficiency but also contributes to the broader objective of enhancing the productivity of the innovation.
- The codebase and data are also made available to readers. This accessibility enables them to replicate or apply the model in their own research, using only the spreadsheet-based user interface of the codebase without the need to interact directly with the code.

The paper is organized as follows. Section 2 evaluates innovation productivity within the context of analytics and the ongoing digital transformation. Section 3 explores the relationship between MO and the design problems of innovation, presenting an implementation framework. Section 4 presents the case study, covering the problem statement, mathematical formulation, computational experiments and a discussion. Finally, Section 5 concludes the paper by summarizing its key points and discussing potential challenges and future research directions.

2. INNOVATION PRODUCTIVITY in the CONTEXT of ANALYTICS

Productivity and innovation are interconnected drivers of prosperity, forming a mutually reinforcing relationship that encompasses several overlapping definitions (Carayannis and Grigoroudis, 2014). Broadly defining, meaningfulness and success of them are intrinsically linked, with each relying on the presence and support of the other.

The innovation process encompasses multiple stages that involve various decision-making problems, with the term decision-making often referred to as design in the context of innovation management. Garud et al. (2013) review innovation process, and during the whole process, there are strategic design problems that need to be addressed, and the efficient and data-driven solution to these problems is of paramount importance for innovation productivity. The human intelligence had been acceptable for a long time to solve these design problems. Unfortunately, the scalability of human problem-solving is inadequate anymore when confronted with the complexity of current decision problems. The digital transformation is reshaping the addressing the design problems of the innovation process. This transformation is led by analytical approaches that promote scalability, automation, prediction, and optimization. Analytical approaches can be broadly classified into three categories (Camm et al., 2020):

- Descriptive Analytics: These approaches revolve around summarizing and visualizing data and thus uncovering and understanding the present situation and performance of a system. The dominating field of study in this area is statistical analysis and data visualization.
- Predictive Analytics: These approaches revolve around learning from historical data to predict future outcomes and behaviors. The dominating field of study in this area is Machine Learning (ML).
- Prescriptive Analytics: These approaches revolve around developing models that use historical data to generate actionable recommendations and optimal courses of action for decision problems. The dominating field of study for this area is OR.

The engines that utilize these analytical approaches have recently started to be classified under the AI framework. The positive perception that the term AI has garnered over the past decade is truly remarkable. It gives the impression that the methods and tools encompassed by this term are entirely novel and groundbreaking. However, many of the analytics encompassed by AI, such as linear regression, clustering, or Markov chains, existed for almost a century. For a comprehensive history and overview of the development of AI, the readers are referred to Haenlein and Kaplan (2019). The main factor that prevented these methods from widespread adoption in the past was the limitations in data availability and computing technology.

Integration of AI into innovation management has the potential to increase overall innovation productivity. In two recent review papers, Haefner et al. (2021) present a review and framework on AI and innovation management, while Mariani et al. (2023) focus on AI in innovation research. Both studies offer valuable insights for AI adoption in innovation and indicate the potential benefits of AI in driving innovation and improving productivity. There has been a recent focus among economists on comprehending the implications of AI for innovation (Cockburn et al., 2019). McKinsey Global Institute is also highly optimistic about the positive impacts of AI on the innovation processes of firms (Jacques et al., 2017). Mariani et al. (2023) recently highlight pioneering organizations like Netflix and Airbnb that have embraced AI to address decision problems within their innovation processes and obtained increased productivity.

Upon revisiting the aforementioned classification of analytics, it is observed that the current trend in AI predominantly revolves around "predictive analytics Within the realm of AI, ML holds a prominent position, especially with the utilization of advanced prediction algorithms such as artificial neural networks. However, prescriptive analytics is still in the process of gaining the widespread adoption and recognition it deserves. It distinguishes itself from the previous two types of analytics by providing decision-makers with ready-made optimal decisions. This unique feature sets it apart. The following section delves into the realm of MO, a prominent field in prescriptive analytics, and examines its connection with innovation productivity.

3. LEVERAGING MATHEMATICAL OPTIMIZATION for INNOVATION PRODUCTIVITY

AI can be broadly defined as the utilization of computers to perform data-driven tasks with specific objectives and constraints, simulating human intelligence without the need for direct human involvement. Within this expansive field, a particularly robust and rapidly gaining popularity subfield emerges known as Mathematical Optimization. MO is the recently popularized naming to describe OR. It mostly aims to combine OR methodologies with computing technology. Its roots can be traced back to the era of the First World War. To obtain a historical perspective of OR on a global scale, the readers are referred to McCloskey (1987). For a more specific insight into the Turkish context of OR, Sabuncuoğlu and Dengiz (2022) provide relevant information.

MO consists of a wide range of methodologies that convert design problems into mathematical formulations and solve them. These formulations define the inputs, objectives, constraints, and decision requirements of the design problem at hand. By solving a formulation, MO seeks to identify optimal recommendations for the decision requirements.

In the absence of ample computing power, MO necessitates extensive expertise and a solid theoretical foundation, rendering its approaches inaccessible to practitioners without a strong background in the field. In fact, in the late 1970s, there were even articles about the lack of a future for OR (Hall and Hess, 1978, Ackoff, 1979). However, in recent times, MO has gained an increased popularity. This is driven by the availability of advanced computing and solver technologies, which offer substantial computational power. Two widely recognized solvers in this field are Gurobi and CPLEX, known for their reliable performance. It is worth noting that there is a wide range of solvers available, both free and paid, catering to various needs and requirements. In benchmark problems, Gurobi has consistently demonstrated superior performance compared to other solvers, establishing itself as the preferred choice for many optimization tasks (Mittelmann, 2020).

Today MO is recognized as one of the fastest growing professions, as highlighted by FORBES (Rothberg, 2021). Furthermore, CBS NEWS has recently acknowledged it as the college major with the highest earning potential as of 2023 (Picchi, 2023). Criticizing the earlier opinions would be unfair, as they were formulated without the benefit of the current favorable conditions. It is unrealistic to expect everyone to possess the foresight and vision of esteemed figures like Professor Cahit Arf (Arf, 1959).

In today's complex business environment, the design problems encountered in innovation processes have become increasingly intricate, surpassing the capabilities of manual or spreadsheet calculations performed solely by humans. They also require near-optimal solutions to be able to gain an advantage in competitive environments. These offer an excellent opportunity to use MO in innovation processes. Today, MO can recommend optimal solutions for large-scale problems, ensuring scalability, and automation, and enabling users to solve their problems without needing an extensive mathematical background.

3.1. MO Implementation in Innovation Stages

At the core of every innovation process is the essential practice of generating and solving ideas, where the decision-making aspect of innovation, often referred to as design by scholars and practitioners, plays a crucial role (Verganti et al., 2020). MO, being an inherent decision-making methodology, presents valuable opportunities for the design problems of innovation. Haefner et al. (2021) highlight the considerable increase in costs associated with innovation management. In this regard, MO holds immense potential as it can deliver significant cost reductions even in complex design problems.

MO can enhance innovation productivity across three stages:

a) *Pre-innovation productivity:* This stage focuses on how MO contributes to the generation of innovation. MO possesses the capability to assess vast amounts of data, consider various constraints and objectives, and make decisions that surpass human intelligence. This opens up new possibilities for advancements and the creation of products with broader applications. For instance, let's consider an EV manufacturer seeking to introduce innovative battery solutions to extend the driving range of their vehicles. By utilizing MO, decision-makers can find the minimum battery requirements that will maximize customer satisfaction by considering factors such as driving speed, traffic conditions, and transportation infrastructure. It can also assist in optimizing material selection in battery production, considering factors such as durability, cost, and environmental impact.

b) *Providing productivity during innovation development:* During product and process development, MO can scale and address problems of large magnitudes and complex issues that surpass human intelligence by leveraging past data and introducing automated solutions. This, in turn, leads to enhanced productivity throughout the innovation development. For instance, in the context of an EV manufacturing facility, MO can determine the optimal integration order of vehicle components, or optimize quality control processes, such as determining the optimal inspection points, sample sizes, and testing frequencies.

c) *Ensuring productivity after innovation deployment:* The true impact of an innovation on the economy is only achieved when it is effectively implemented in practice. If an innovation is not deployed properly, it may underperform compared to existing products and processes. For instance, consider the challenge of positioning charging stations for electric vehicles (EVs). If this problem is not accurately addressed, EVs may face difficulties in finding convenient charging locations, hindering their market acceptance. Another example involves optimizing production plans by analyzing past data, market trends, and customer preferences. In all these design problems, MO can play a vital role in providing solutions.

3.2. MO-Driven Framework for Innovation Productivity

Next, a framework driven by MO for innovation management is introduced. Note that MO in decision-making is not a new concept, as it has a longstanding history under the OR framework. Only an adaptation of it to innovation management is presented below.

The framework consists of the following steps. Please note that only Step 3 requires expertise in MO. Steps 1, 2, 5, 6, 7, and 8 are generally the responsibility of decision-makers and users of the MO model. Steps 2, 4, and 6 require programming skills, without any specific MO prerequisites.

1. *Problem Definition*: Define innovation challenges and opportunities, as well as identify design problems that can benefit from increased productivity. Establish the ground rules of the defined problem, including the objective of the design, the decisions that need to be made, and the constraints that limit available options are identified.
2. *Data Collection and Processing*: Gather relevant data related to the innovation design problem, including historical data and future predictions. Analyze the data and extract information that is relevant to the ground rules defined in the problem definition.
3. *Mathematical Formulation Development*: Formulate the identified innovation design problem as a mathematical model that includes decision variables, objectives, and constraints.
4. *Translation of Mathematical Formulation to Computer*: Translate the mathematical formulation into a format that solver technologies can comprehend by utilizing a computer programming language. For instance, to solve the model using Gurobi in Python, one can employ the Gurobi Python API (gurobipy).
5. *Model Solving Using Computing Technology*: Solve the model using computing technology, for example, by utilizing the Gurobi solver.
6. *Reporting, Results Evaluation, and Validation*: Translate the results into a format that can be understood by individuals without expertise in computer programming and MO. This step conducts studies to validate that the model behaves as intended and finds solutions that can be implemented in practice. Use reporting and visualization techniques. Provide detailed analyses and evaluations that demonstrate the impact of decisions on the objective and present the productivity gains achieved through the use of MO.
7. *Implementation and Execution*: Implement the recommended decisions generated by MO into the corresponding design problem the innovation process.
8. *Performance Evaluation and Feedback*: Collect feedback from the implementation process to refine the mathematical model and update the input data based on the resources utilized during the implementation of the recent MO run. This feedback will inform future iterations of the optimization runs, allowing for continuous improvement of the model's performance.

Figure 1 presents the practical implementation of the framework. The blue shaded boxes represent components that can be handled by software teams without requiring expertise in MO. The green-shaded components require expertise in MO. In a typical design problem addressed with MO, there are two types of data sources: dynamic and stable. Stable data refers to fixed data that is used regardless of user input or the results of previous decisions. For example, for a problem of determining optimal charging station locations for EV vehicles in Ankara, geographical data of potential charging locations is stable data. The second data type is dynamic data, which can be inputted by the user or based on past decisions. For instance, the minimum number of EV stations required in Ankara can be provided by the user. Once the data is collected from the data sources, input adapters should come into play. Input adapters are computer code snippets that translate the data into the MO computer model. Similarly, the MO model should be initially developed and formulated on paper and then translated into computer code using solver APIs. Once the solvers solve the problem optimally, a typical MO model produces two outputs: optimal decisions and the optimal objective function. The former provides recommendations to decision-makers for the defined and formulated decision problems, while the latter indicates the performance of the recommended decisions. Finally, a typical MO model should include an output adapter that converts the solver's results into more easily understandable reports and visualizations, enabling decision-makers to comprehend the results effectively.

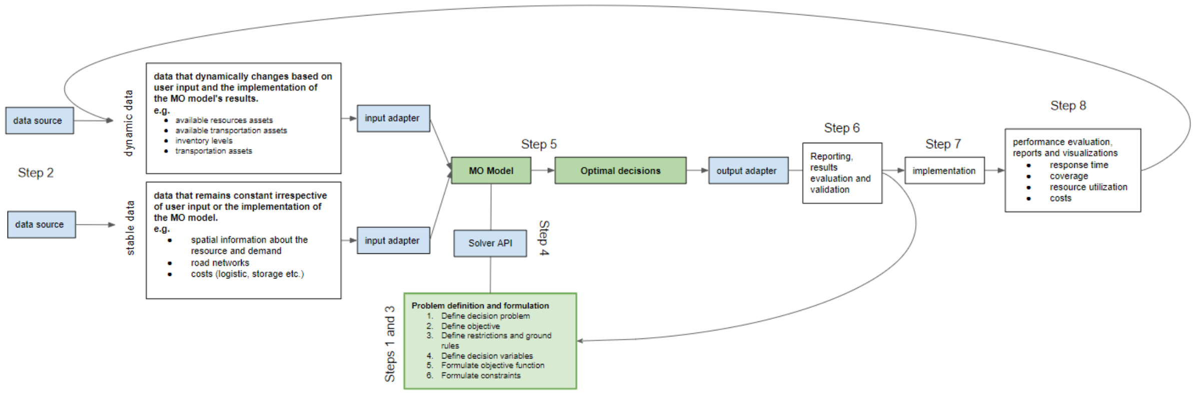

Figure 1. MO implementation framework

4. CASE STUDY: UTILIZING UAVs for BORDER PATROLLING in TÜRKİYE

UAV refer to aircraft that operate without a human pilot onboard and instead rely on autonomous systems. They are being employed for a diverse array of intricate missions worldwide. They have significantly transformed various domains with their innovative features on automation, versatility, safety, efficiency, and other technological advancements. They conduct autonomous or remote-controlled flights, replacing human pilots. Evers et al. (2015) and Elmokadem and Savkin (2021) highlight their increasing autonomy. They are versatile, serving diverse purposes in military operations, search and rescue missions, border patrolling, and wildlife inspection. They enhance safety by operating in hazardous environments, reducing risks to human lives. They require fewer resources, covering larger areas at lower costs and in less time. Ongoing technological advancements in their equipment such as improved batteries and miniaturized sensors drive continuous innovation and open up new avenues for research and development. MO has the potential to enhance the efficiency of all the factors mentioned above, leading to an increased productivity of UAV innovation.

In this paper, the focus lies on enhancing the productivity of UAVs through addressing design problems in the post-innovation stage. Specifically, the efficient deployment of a UAV fleet for border patrolling activities in Türkiye is addressed. This problem can be categorized as a variant of the Vehicle Routing Problem with Profits (VRP) and shares similarities with the Team Orienteering Problem (OP). Comprehensive reviews of VRP and Team OP can be found in Braekers et al. (2016) and Gunawan et al. (2016), respectively. An example of VRP with profits is provided by Stavropoulou et al. (2019). Coutinho et al. (2018) and Rojas Viloria et al. (2021) offer comprehensive reviews on UAV routing and scheduling.

The study diverges from the literature in several aspects. The UAV prize collection and routing literatures typically consider non-monitored terrains, movement between two targets, single trajectories between targets, and fixed prices. In contrast, uncertainty in prize detection is considered. Furthermore, a monitored terrain is considered by incorporating the risk of radar threats, an aspect seldom addressed in the literature. Additionally, the scope is expanded by including multiple UAVs in the analysis, a factor often overlooked in recent research. Also, different mission aspects including fleet size, mission duration, and mission safety are considered together. Table 1 provides a summary of closely related studies to the paper based on several factors, including the UAV's operational terrain, movement (between origin-destination or multiple targets), problem classification, UAV fleet size, and the considerations applied, whether as objectives or constraints. These studies have employed mathematical optimization approaches for routing to enhance the efficiency of UAV utilization. The "Terrain" column displays the modeling of the movement terrain. This can be either continuous or discretized, with the discretization achieved through methods like grid-based, trajectory selection, or waypoints. The "Movement" column specifies whether the movement is between two targets or involves visiting multiple targets. The "Class" column categorizes problems into four types: shortest path (SP), traveling salesperson problem (TSP), vehicle routing problem (VRP), or orienteering problem (OP). "Fleet size" denotes the number of UAVs examined in each study.

Among these studies, this study shares some similarities with the work conducted by Moskal et al. (2023). A similar terrain representation is utilized in this study by considering waypoints that UAVs can change their course of direction, and employ similar approaches to model the information search and collection process and measure the radar detection threat. However, the model and experiments exhibit significant differences. The study extends beyond by incorporating a fleet of UAVs, whereas their study focuses on TSP with a single UAV. Moreover, the problem is approached from a multi-objective perspective, extracting the tradeoffs among mission duration, mission safety, and fleet size. The primary goal is to recommend an ideal fleet size, addressing a practical high-level design problem in UAV post-innovation deployment. Additionally, a unique case study focused on border patrolling in Türkiye is developed, and the associated data and solution software developed are openly shared.

Table 1. Comparative table for related UAV literature

Study	*Terrain*	*Movement*	*Class*	*Fleet size*	*Considerations*
Mittal and Deb (2007)	Continuous	Origin-destination	SP	Single	Mission duration Mission safety
Pfeiffer et al. (2009)	Continuous	Origin-destination	TSP	Single	Mission duration Mission safety
Tezcaner and Köksalan (2011)	Discretization by grids	Multiple targets	TSP	Single	Mission duration Mission safety
Guerriero et al. (2014)	Continuous	Multiple targets	VRP	Multiple	Mission duration Information collection Deployed UAVs
Moskal and Batta (2017)	Discretization by waypoints	Multiple targets	OP	Single	Mission duration Information collection
Dasdemir et al. (2020)	Continuous	Multiple targets	TSP	Single	Mission duration Mission safety
Dasdemir et al. (2022)	Discretization by trajectory	Multiple targets	OP	Single	Information collection Mission duration Mission safety
Tezcaner Öztürk and Köksalan (2023)	Continuous	Origin-destination	TSP	Single	Mission duration Mission safety
Moskal et al. (2023)	Discretization by waypoints	Multiple targets	OP	Single	Information collection Mission duration Mission safety

The case study involves design challenges in both high and low levels. The high-level design problems are determining the optimal fleet size, mission duration and risk tolerance to attain the desired performance in information collection. The low-level design problems pertain to the operational aspects within a given fleet size, mission duration and risk tolerance. These encompass selecting the targets to visit, determining the number of searches at the selected targets, allocating UAVs to the selected targets, and making routing decisions that dictate the optimal route for each UAV to visit the assigned targets.

The solution process involves creating a mathematical formulation and a computer program that translates the formulation into code, leveraging the power of the Gurobi solver. The development of the mathematical formulation necessitates expertise in the field. Once the model is developed, the subsequent steps involve straightforward computer programming tasks, enabling automated solving by simply adjusting the input parameters. Similar to other AI engines, the user interacts with the model by supplying inputs and prompts, while the underlying model works to generate the desired solutions. The data and computer code of Türkiye case study are provided openly to readers, promoting the reproducibility of the results and aiding researchers in further developing the model.

This case study contributes to the existing UAV routing and scheduling literature by introducing a novel MO model and offering a practical demonstration. While drawing from the work of Moskal et al. (2023) who study an information collection problem with a single UAV, the study goes beyond by incorporating a fleet of UAVs and addressing the high-level design problem of optimizing the fleet size. In addition, the approach diverges from traditional models by considering uncertain prizes, where the presence of a prize can only be confirmed after a successful search, a notable deviation from the conventional fixed prize assumption. Furthermore, a monitored terrain is considered by incorporating the risk of radar threats, an aspect seldom addressed in the literature.

4.1. Problem Statement

The objective of the mission is maximizing the total amount of utilized information from the mission terrain using a fleet of UAVs, while satisfying the restrictions on mission duration and likelihood of being detected. In this section, the context of the problem, including the mission terrain and operational structure, is introduced.

4.1.1. Mission Terrain

The mission terrain is presented in Figure 2, which showcases the ten potential search locations referred to as targets from this point onward. Among these targets, a total of seven search locations along Türkiye's borders, as well as three additional search locations in the Aegean, Mediterranean, and Black Seas, are considered. Initially, all UAVs are stationed at Ankara, marked as the home base (h) on the map. All UAVs depart from the home base, visit a set of target regions to search and collect information, and then return to Ankara to complete the mission.

The Bayraktar Akıncı is considered as the UAV of choice. While this UAV is primarily designed for target neutralization missions due to its exceptional payload capacity and launching capabilities, it is assumed that decision-makers are selecting a fleet of Akıncı UAVs to optimize their operational use specifically for border patrolling and information collection purposes in Türkiye. The Bayraktar Akıncı can fly with a flight speed ranging from approximately 280 to 360 km/h and can operate for 24 hours (Baykar, 2023). Its ample payload capacity allows for the integration of search and collection sensors. In this case study, the flight speed is set to 360 km/h and the maximum mission time to 24 hours.

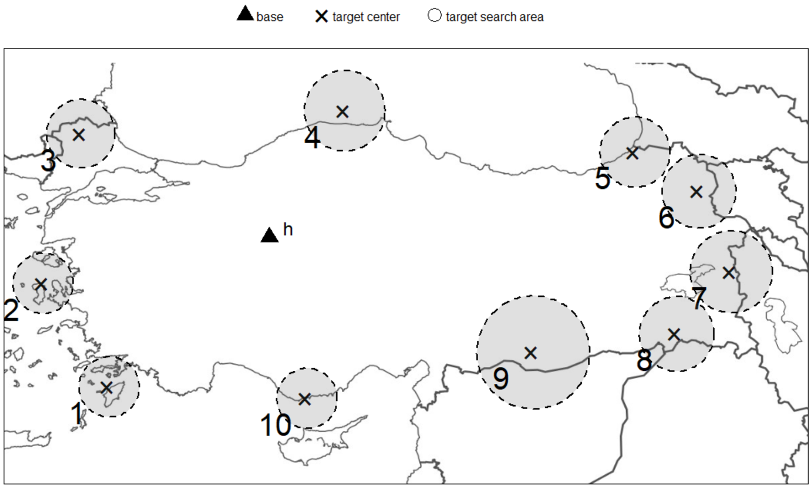

Figure 2. Mission terrain with 10 search targets

Each target j is characterized by two attributes: the probability of containing information (ρ_j), which represents the chance of the existence of a source of information at target region j, and the radar detection threat (λ_j), which represents the detection per unit of time the UAV is exposed to while conducting search activities in region j. Once a target is chosen for information search, the UAV proceeds to navigate towards the designated center of that region. Upon arrival, it commences the search and recording process to gather the necessary information.

It is assumed that the UAV conducts a circular search pattern, with a fixed duration of 1 hour allocated for this purpose. The approximate lengths of the borders close to the targets are scaled to fit within the range of [80, 150] kilometers and the range of [0.25, 1], and use the scaled values as the radius for the circular search areas and as the likelihood of information existence, respectively. Similarly, the elevations of the mountains near the targets are scaled to range [0.02, 0.05] kilometers, serving as the detection rates in the corresponding search regions.

4.1.2. Information Search and Collection

In practical scenarios, UAVs are susceptible to various sources of volatility. To account for one of these factors, uncertainty in the availability of information is considered. The probability of successfully detecting information is determined by both the availability of the information and the search sensor carried by the UAV.

Each UAV is equipped with a search and a collection sensor. The effectiveness of the search sensor for the search at target region j ($e_{s,j}$) impacts the chance of successfully detecting the available information source. On the other hand, the effectiveness of the collection sensor (e_c) impacts the percentage of the detected source is utilized in a visit.

Multiple visits to the same target region are allowed due to the imperfections of the search and collection sensors. Equation 1 is used to compute $e_{s,j}$ (Xia et al., 2017). In the equation, the effective range of the search sensor (W), the flight speed of the UAV (v), and the radius of the target region j (r_j) is used. In this study, W and v are set to 80 km and 360 km/h.

$$e_{s,j} = 1 - (e^{\frac{-W \cdot v}{\pi \cdot r_j^2}}) \quad (1)$$

The total expected information collection is maximized, which serves as a deterministic approximation to account for the inherent uncertainty explained above in the information detection and collection. It is assumed that the presence of a single piece of information source that is subject to search and collection upon detection. This assumption aligns with the focus of search theory literature, which commonly addresses the task of finding a single source. For instance, Xia et al. (2017) also consider the assumption of one source of information when conducting information search using UAVs.

Let $I_{j,m}$ represent a discrete random variable that indicates the amount of information collected from target j during visit m. In the case where a valuable information is detected during the first visit, $I_{j,1}$ is set to $1 \cdot e_c$ as e_c of a one unit of information can be collected. It is assumed that the collectible information diminishes exponentially with each subsequent visit, irrespective of the outcome of the search process during the previous visit. This collection pattern is expressed through the exponentially decreasing function $(1-e_c)^{m-1} - (1-e_c)^m$, which is adopted from Moskal et al. (2023). Consequently, the probability mass function of $I_{j,m}$ can be formulated as in Equation 2.

$$P(I_{j,m}) = \begin{cases} \rho_j \cdot e_{s,j}\,,\ if\ I_{j,m} = (1-e_c)^{m-1} - (1-e_c)^m \\ 1 - \rho_j \cdot e_{s,j}\,,\ I_{j,m} = 0 \\ 0\,,\ otherwise \end{cases} \quad (2)$$

Consequently, the expected amount of collected information from vehicle k during its m^{th} visit to target j is calculated using the formula $E[I_{j,m}] = \rho_j \cdot e_{s,j} \cdot ((1-e_c)^{m-1} - (1-e_c)^m)$.

4.1.3. Search Time and Travel Times

Each UAV allocates a specific duration to the search and recording process at each visited target. The time allocated for each revisit is independent, emphasizing the necessity of conducting the search and recording process on every visit. This restarting assumption remains valid even if previous visits have detected information, as the source of information may have relocated or adopted camouflage measures upon realizing the presence of the UAV in the region.

However, a gradual reduction of α% is assumed in the duration of the search and recording process with each revisit. This reduction acknowledges that UAVs become more acquainted with the region and can focus their efforts on specific areas. The time that a UAV spends at target j during its m^{th} visit is represented as $s_{j,m} = s_d \cdot \alpha^{(m-1)}$, where s_d represents the specific duration of a search and collection process and s_d is set to 1 hour and α is set to 80%.

Each UAV needs to travel to the center of the target, as these central waypoints allow for changes in the UAV's flight direction. Let $t_{i,j}$ represent the travel duration from target region i to target region j. To determine the travel distance between pairs of targets, the Euclidean distances calculated using the waypoints. Dividing this distance by the speed of the vehicle provides us with the corresponding travel duration. In order to account for the consistent speed of the vehicle, a discount to longer travel distances is implemented. Specifically, distances exceeding the minimum distance and extending up to the maximum distance in the terrain are subject to a discount of up to 30% of their Euclidean distance. This discount is applied in a linear manner, gradually increasing from the minimum distance to the maximum distance. It is assumed that there are no flight dynamics constraints such as turning angles or other physical limitations that UAVs may encounter during their maneuvers.

4.1.4. Radar detection threat

Similar to Pfeiffer et al. (2009) and Moskal et al. (2023), the Poisson process to represent the detection threat is adopted. Let r^k denote the random variable counting the number of detections that vehicle k is exposed to, and $P(r^k = n)$ as the probability of vehicle k experiencing n detections. Moskal et al. (2023) demonstrates, the random variable r^k exhibits the properties of a Poisson process and thus follows a probability distribution. Let θ^k denote the average number of detections experienced by UAV k. The distribution can be expressed as in Equation 3.

$$P\left(r^k = n\right) = \frac{1}{n!} \cdot \theta^k \cdot e_f^{-\theta^k}, n = 0,1,2,\ldots \tag{3}$$

4.2. Mathematical Formulation

Table 2 presents the mathematical notation in and then present the formulation.

Table 2. Mathematical notation

Notation	*Definition*
Sets	
N	Set of nodes including targets and home base.
K	Set of vehicles.
M	Set of revisits.
T	Set of time steps.
Parameters	
$I_{j,m}$	Expected information collected from target j at visit m.
F	Maximum allowed mission duration, h (hour).
β	Maximum risk acceptable for the probability of being detected.
e_c	Collection sensor effectiveness.
e_s	Search sensor effectiveness.
$s_{j,m}$	Search and recording duration in terms of h that a UAV spends at target j at its m^{th} visit.
$d_{i,j}$	Travel duration in terms of h from target region i to j.
v	UAV flight speed, km/h
$\lambda_{i,j}$	The number of detections per unit of time the UAV is exposed to while traveling from target i to j.
λ_j	The number of detections per unit of time the UAV is exposed to when conducting search activities in region j.
δ	Sufficiently small positive constant.
Decision Variables	
θ^k	Average number of detections experienced by UAV k.
t_h	Arrival time of the UAV returning to the home base at the latest.
$y_{j,m}^k \in \{0,1\}$	Binary variable indicating whether vehicle k searches target j for the m^{th} time.
$x_{t,i,j}^k \in \{0,1\}$	Binary variable indicating whether vehicle k travels from target i to target j at time step t.

Armed with above notation, the mathematical formulation is ready to be presented.

$$Max\ \sum_{j\in N_t} \sum_{m\in M} I_{j,m} \sum_{k\in k} y_{j,m}^k - \delta \cdot t_h \tag{4}$$

s.t.

$$\theta^k \leq -ln(1-\beta) \qquad \forall k \in K \tag{5}$$

$$\theta^k = \sum_{t\in T} \sum_{i\in N} \sum_{j\in N\setminus\{i\}} \lambda_{i,j} \cdot d_{i,j} \cdot x_{t,i,j}^k + \sum_{t\in T} \sum_{m\in M} \lambda_j \cdot s_{j,m} \cdot y_{j,m}^k \qquad \forall k \in K \tag{6}$$

$$t_h \leq F \tag{7}$$

$$t_h \geq \sum_{t\in T} \sum_{i\in N} \sum_{j\in N\setminus\{i\}} d_{i,j} \cdot x_{t,i,j}^k + \sum_{j\in T} \sum_{m\in M} s_{j,m} \cdot y_{j,m}^k \qquad \forall k \in K \tag{8}$$

$\sum_{k\in K} y_{j,m}^{k} \leq 1$ $\quad \forall\, j \in N\backslash\{h\}, m \in M$ (9)

$\sum_{k\in k} y_{j,m}^{k} \geq \sum_{k\in k} y_{j,m+1}^{k}$ $\quad \forall\, j \in N\backslash\{h\}, m \in M$ (10)

$\sum_{m\in M} y_{j,m}^{k} \leq \sum_{t\in T}\sum_{i\in N} x_{t,i,j}^{k}$ $\quad \forall\, j \in N\backslash\{h\}, \forall k \in K$ (11)

$\sum_{j\in N\backslash\{h\}} x_{1,h,j}^{k} = \sum_{t\in T\backslash\{1\}} \sum_{\in N\backslash\{h\}} x_{t,j,h}^{k}$ $\quad \forall k \in K$ (12)

$\sum_{j\in N_t} x_{1,h,j}^{k} = 1$ $\quad \forall\, k \in K$ (13)

$\sum_{i\in N} x_{t,i,j}^{k} = \sum_{i\in N} x_{t+1,j,i}^{k}$ $\quad \forall\, t \in T, \forall\, j \in N\backslash\{h\}, \forall\, k \in K$ (14)

$x_{t,i,j}^{k} \in \{0,1\}$ $\quad \forall\, t \in T, \forall i \in N, \forall j \in N, i \neq j, \forall k \in K$ (15)

$y_{j,m}^{k} \in \{0,1\}$ $\quad \forall\, j \in N\backslash\{h\}, \forall\, m \in M$ (16)

Objective Function 4 maximizes the total expected collected information from the mission terrain. It includes a secondary component that considers the return time of the UAV to the base, prioritizing solutions with smaller total duration in case multiple optimal solutions have the same expected collected information.

Constraint 5 imposes a limit on the average detection experienced by the UAVs, while Constraint 6 calculates the average detection rates of the UAVs. These two constraints serve as a linear approximation to the radar restriction constraint described in Equation 17.

$P\left(r^{k} \geq 1\right) \leq \beta$ $\quad \forall k \in K$ (17)

Proposition 1. Constraints 5 and 6 are valid equations to replace Equation 17.

Proof. Equation 17 indicates that the probability of a vehicle being detected at least once must be lower than the tolerance threshold β set by decision makers. Constraints 5 and 6 are valid equations to replace Equation 17. By subtracting both sides of Equation 17 from 1, it is found that 1 - $(r^{k} \geq 1) \leq (1-\beta)$. Since 1 - $P(r^{k} \geq 1)$ is equivalent to $P(r^{k} = 0)$, the left side can be replaced with $P(r^{k} = 0)$, resulting in the inequality $P(r^{k} = 0) \leq (1-\beta)$. Furthermore, $P(r^{k} = 0)$ is equal to θ^{k} as defined in Equation 3. The conclusion can be drawn with the equation $\theta^{k} \leq (1-\beta)$, as presented by Constraint 5.

Constraint 7 imposes a limitation on the mission time by restricting the largest returning time to the home base among all UAVs in the fleet. In other words, the largest returning time to the base is determined as the largest flight duration among all UAVs and is subject to the constraint defined by parameter F. The calculation of the largest returning time to the home base is carried out by Constraint 8, which is derived with the assistance of the second part of Objective Function (Equation 4).

Constraint 9 guarantees that each revisited of a target can only be performed once by a single vehicle. For instance, if a target region is visited for the first time, it can only be done by one vehicle. Similarly, if it is visited for the second time, it must also be performed by only one vehicle.

Constraint 10 establishes the sequence of revisits, ensuring that subsequent revisits to a target can only be conducted if the earlier visits have already been completed. Constraint 11 ensures that if a vehicle performs a search at a target, it must have arrived at that target. This constraint establishes the requirement that a vehicle must reach the target before conducting any search operations.

Constraint 12 states that any vehicle that leaves the home base at the first time step must return to the base in one of the subsequent time steps. This constraint ensures that vehicles that depart from the base initially will eventually make their way back to the base after completing their missions.

Constraint 13 ensures that all UAVs in the fleet depart from the base at the first time step. This constraint guarantees that every vehicle initiates its mission at the beginning of the planning horizon.

Constraint 14 represents flow balance equations that ensure the consistency of vehicle movements. It enforces that when a vehicle arrives at a target at a particular time step, it must depart from that target in the subsequent time step. This constraint maintains the continuity of vehicle movements between targets, facilitating a coherent and efficient mission plan. Equations 15 and 16 define decision variables.

4.3. Data and Software

A computational application has been developed to accompany the mathematical model and case study, which is publicly available on GitHub[2] to support reproducibility efforts. This codebase, programmed in Python, leverages the Gurobi Optimizer via the gurobipy API to solve the mathematical model. Designed as a command-line application, the codebase processes input data from a spreadsheet, computes optimal solutions, and outputs these solutions into a new spreadsheet file. This streamlined process allows users to adjust input parameters without direct code interaction, transforming the codebase into an accessible, spreadsheet-integrated primitive software tool. This design is particularly beneficial for fellow researchers, enabling them to replicate the findings, apply the model to analogous problems, or adapt the dataset to their specific research contexts.

To operate this primitive software, users must ensure the installation of the required computational environment on their systems, including Python, Gurobi, and an active Gurobi license. The input file, located in the designated input folder, comprises three sheets: the first two sheets pertain to target-specific data, while the third sheet contains general parameters like the number of targets and the selected run mode. The software offers two operational modes: "single_objective", which solves the model with predefined parameters, and "multi_objective", which iteratively modifies parameters such as the time limit, detection limit, and vehicle size to analyze trade-offs in information collection, mission duration, mission safety, and fleet size. Detailed operational guidelines are available in the accompanying read me file.

In addition to the codebase, two sets of raw data are provided: one pertaining to the case study and another for a larger, hypothetical instance. These datasets are further elaborated upon in subsequent sections. The raw data requires transformation into a compatible format for the model code, a process facilitated by the provided scripts in the instance generator folder.

4.4. Computations

The models are solved with the GUROBI Optimizer 10.0.1 (Gurobi Optimization, 2024) through the developed Python software on a Dell 32-core computer running Linux Centos 7.5.x with a processor Intel Xeon Gold 6130 CPU, @32 x 2.10GHz and 192 GB usable RAM (CCR, 2024).

To review the parameter settings, $N = \{h, 1, 2, \dots, 10\}$, $M = \{1, 2, 3\}$, and $T = 32$. Setting $T = 32$ is sufficient as it is larger than the suggested value $(|N/\{h\}| \cdot |M| + 1)$ by Moskal et al. (2023) for a similar modeling approach. This ensures that the time step index does not restrict the movement of the UAVs. It is assumed that the vehicle is the Bayraktar Akinci with a speed of $v = 360$ km/h. Geographical information on the terrain was extracted from Google Maps, and Euclidean distances between target pairs were used. As vehicle speed stability decreases fuel consumption in practice, discounts to longer travel distances are applied. These discount rates increase linearly from the minimum distance to the maximum distance in the terrain, where the maximum distance is discounted 30%. For the search sensor parameters, W is set to 80 km, the search duration s_d is set to 1 hour, and α is set to 80%.

Different restriction combinations are considered, and the model is solved for each combination. $K = \{1, \dots, k_{max}\}$, where $k_{max} \in \{2, 3, 4, 5, 6, 7, 8\}$, $F \in \{4, 8, 12, 16, 20, 24\}$ and $\beta \in \{0.01, 0.02, 0.03, 0.04, 0.05\}$ are used. The model is solved for each combination of these restrictions in order to extract insights about their impact and help decision makers in their high-level decisions. In all iterations, termination time for solver is set to to one hour. The decision to limit the runs to 1 hour was driven by the extensive nature of the computational experiments conducted. at a maximum of 1 hour per run, the total computation time could extend to 210 hours (approximately 8.75 days) in the worst-case scenario, since some cases may be resolved more quickly.

4.4.1. General Results

The analysis is initiated examining the results in a broader manner, with a focus on the distributions of three pivotal output metrics: expected collected information, solution time, and termination gap (see Figure 3). It is imperative to note that in the specific case study, the maximum expected information collection value stands at 2.106, and this maximum is achieved when all targets are visited. These distributions of three metrics offer valuable insights into the behavior of the model across multiple iterations and the variability in its performance, as quantified by these three metrics.

It is worth noting that the majority of solutions exhibit a minimal gap, typically hovering around 0%. Nevertheless, there exist instances characterized by a significantly larger gap. Furthermore, while the majority of runs conclude expeditiously, a few require a considerably longer duration to reach a solution. The average solution time across the 210 runs is approximately 18 minutes (1097 seconds) and the median

[2] https://github.com/edasdemirlab/production-innovation-uav-2023

is only 5 seconds. Of note, the distribution of expected collected information exhibits a somewhat bimodal pattern, featuring two prominent peaks. In summary, it is evident that the results exhibit variability across all three metrics. This variability primarily stems from the influence of constraints pertaining to mission time, detection probability, and fleet size considerations.

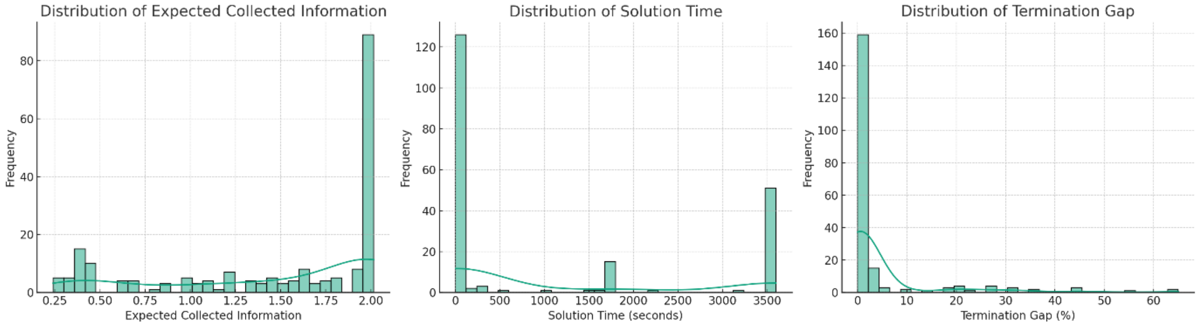

Figure 3. Distributions of three pivotal output metrics

Subsequently, the impact of three constraints on the three-key metrics of interest is investigated. The Table 3 presents the Pearson correlation coefficients. Notably, a robust positive correlation emerges between expected information collection and the "Mission Time Limit," while a moderately positive correlation is observed with the "Number of Vehicles." This observation is logical, as an increase in the allowed flight duration and fleet size facilitates the visiting of more targets and the subsequent collection of more information. Conversely, a weak negative correlation is detected between solution time and both the "Detection Count Limit" and the “Number of Vehicles”. This indicates that when the fleet size is limited and radar constraints are stringent, the model faces difficulties in identifying optimal solutions within the prescribed one-hour timeframe. Similarly, the "Mission Time Limit" exhibits a negative correlation with the termination gap, implying that the utilization of restrictive time limits leads to either the model's struggle in discovering optimal solutions or in substantiating their optimality.

Table 3. Correlation coefficients between the restrictions and three metrics

	Expected Collected Information	*Solution Time*	*Gap*
Number of Vehicles	0.284	-0.147	0.043
Mission Time Limit	0.746	-0.007	-0.280
Detection Count Limit	0.175	-0.283	0.055

Next, potential high and low-level design challenges that could manifest during the post-innovation phase of UAV deployment are investigated, with the aim of evaluating the results from a managerial perspective.

4.4.2 High-level Design Problems

The high-level design problems in post innovation stage of UAV deployment for the decision makers are determining the optimal fleet size, mission duration and risk tolerance to attain the desired performance for decision-makers in information collection.

Figures 3 and 4 present the results illustrating the relationship between total expected information collection and fleet size. Since this relationship is directly influenced by the limitations of mission duration and risk tolerance, two figures are provided.

In Figure 4, it is assumed that decision-makers are not risk-seeking and therefore enforce a restrictive detection limitation with $\beta = 0.1$. The results indicate that, for a fixed fleet size, the collected information tends to increase with longer flight durations. However, this increase is limited when the fleet size is small. For instance, when $|K| = 2$, increasing the mission duration limit from 4 to 12 helps increase the information collection. However, increasing it from 12 to 24 does not offer any additional benefits in achieving higher information collections. This behavior remains consistent when the fleet size is increased, with the advantage of higher information collections achievable in shorter durations due to the presence of more UAVs. With a greater number of UAVs, the targets can be divided among them, resulting in shorter routes for each UAV and reduced exposure to detection threats. It is noticed that the maximum achievable information collection in the terrain, which is approximately 2, can only be attained when the fleet size consists of 8 UAVs and the mission duration limit is set to 12 or greater. In essence, decision-makers should prioritize building a fleet of 8 UAVs and limit the mission duration to 12, as increasing it beyond that threshold does not yield any additional advantage in fully utilizing the information from the mission terrain.

Figure 5 showcases the results when $\beta = 0.5$, indicating that decision-makers are less concerned about detection threats as the mission primarily takes place in Türkiye and the terrain is non-hostile. Even a small fleet size can now achieve the maximum attainable information collection. For instance, decision-makers can establish a fleet consisting of two UAVs and set a mission duration limit greater than 20, which would be sufficient to fully utilize the terrain. Alternatively, if decision-makers prefer a shorter mission duration and are willing to have a larger number of aircraft in their fleet, four UAVs and a 16-hour limitation or five UAVs and 12-hour limitation would be enough to collect the available information. It is worth noting that the results indicate no additional benefit in increasing the fleet size from four to eight UAVs, so there is no need to include four extra UAVs in the fleet. This could result in significant cost savings considering the setup and operational expenses associated with the additional UAVs.'

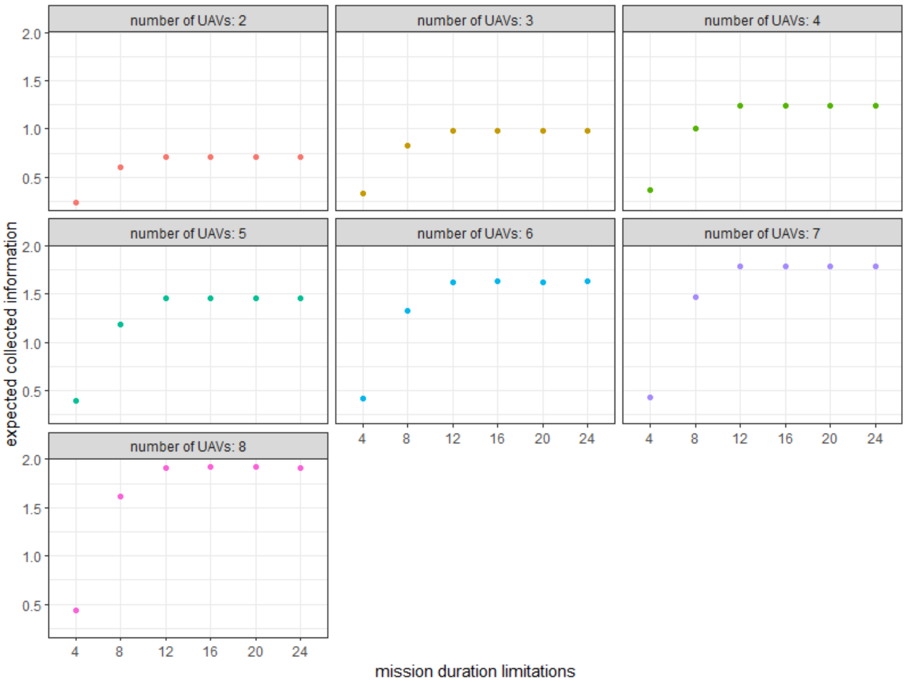

Figure 4. Relationship between fleet size and expected information collection when $\beta = 0.1$

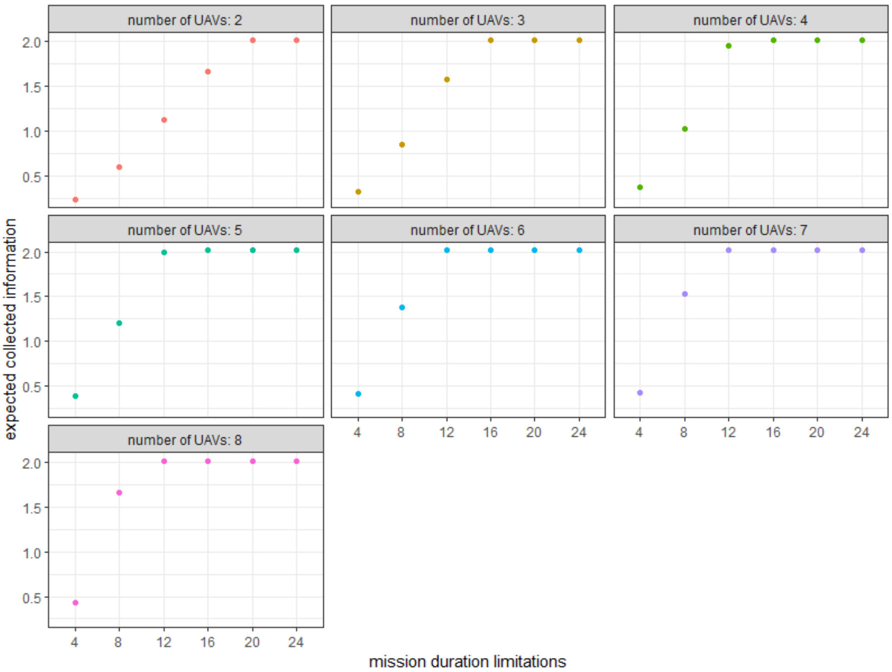

Figure 5. Relationship between fleet size and expected information collection when $\beta = 0.5$

These analyses serve as compelling demonstrations of the MO's ability to provide optimal recommendations for critical design problems. Typically, determining a fleet size while considering flight duration and radar detection threat is a highly complex task for human intelligence. However, with the utilization of MO, the problem is efficiently solved. These iterative runs encompass a total of 210 runs, all of which were resolved within 1 hour. The computational results are presented in Figure 6 using boxplots, which effectively capture the variability attributed to the fleet size. The mean and median solution time across the 210 runs is 1097 and 5 seconds, respectively. In many instances, the solver finds the solution within seconds. While there are cases where the solution time reaches the maximum limit, 1 hour is still a reasonable timeframe for making strategic decisions regarding fleet size and mission duration.

The computational performance can be further enhanced by understanding the factors that affect the computational requirements. The solver may face challenges in finding the initial solution, which can be addressed using heuristic approaches, or it may find the optimal solution quickly but struggle with proving its optimality, which can be improved through the use of valid equations and cuts. Although these aspects are beyond the scope of this study, it is worth mentioning that performance improvements are possible. Furthermore, solver technology is advancing at a rapid pace. Problems that were unsolvable or had very long solution times just a couple of years ago can now be solved much more efficiently due to advancements in computing power and solver technology.

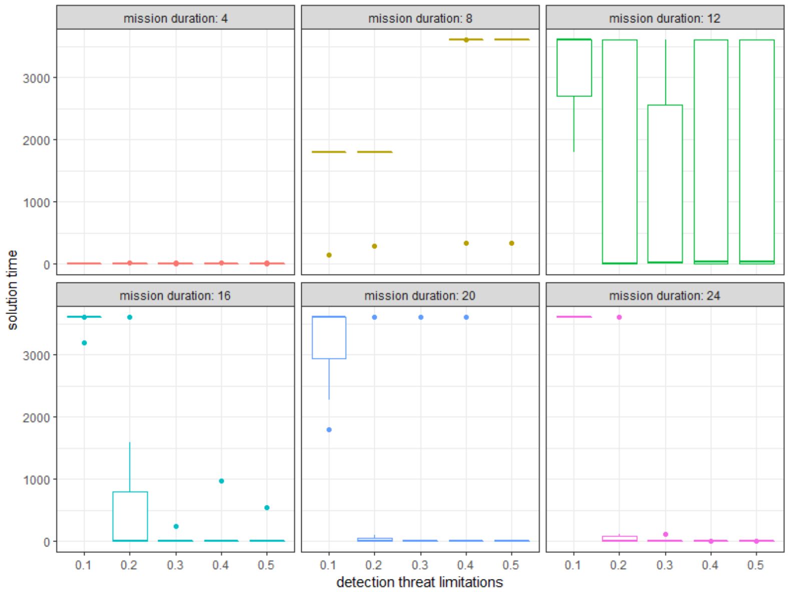

Figure 6. Computational requirements of the model

4.4.3 Low-level Design Problems

The low-level design problems in the post-innovation stage of UAV deployment for decision-makers involve making optimal decisions at the operational level. These decisions revolve around the allocation of the UAV fleet to target locations. This includes determining which targets should be visited, how many times they should be visited, assigning them as tasks to specific UAVs, and determining the visiting order or route for each UAV.

To showcase the effectiveness of MO in providing optimal recommendations to decision-makers, the objective and decision space of the case with fleet size of 4, a risk tolerance of 0.5, and a mission duration limitation of 16 hours is presented. The results in the objective space are as follows: total collected expected information, solution time (in seconds), longest flight duration among UAVs (in hours), and largest detection exposure among UAVs are 2.02, 4.74, 14.99, and 0.25, respectively.

Figure 7 displays the allocations of UAVs to targets and the routes they follow. The results indicate that UAV 1 visits targets 5, 4, and 2, and then returns to the base. It performs 3 searches at targets 5 and 2, and a single search at target 4. UAV 2, on the other hand, visits targets 9, 6, and 8, and then returns to the base. It conducts 1 search at target 9, 3 searches at target 6, and 2 searches at target 8. Finally, UAV 3 visits targets 10, 1, and 3, and then returns to the base. It carries out 3 searches at all three targets.

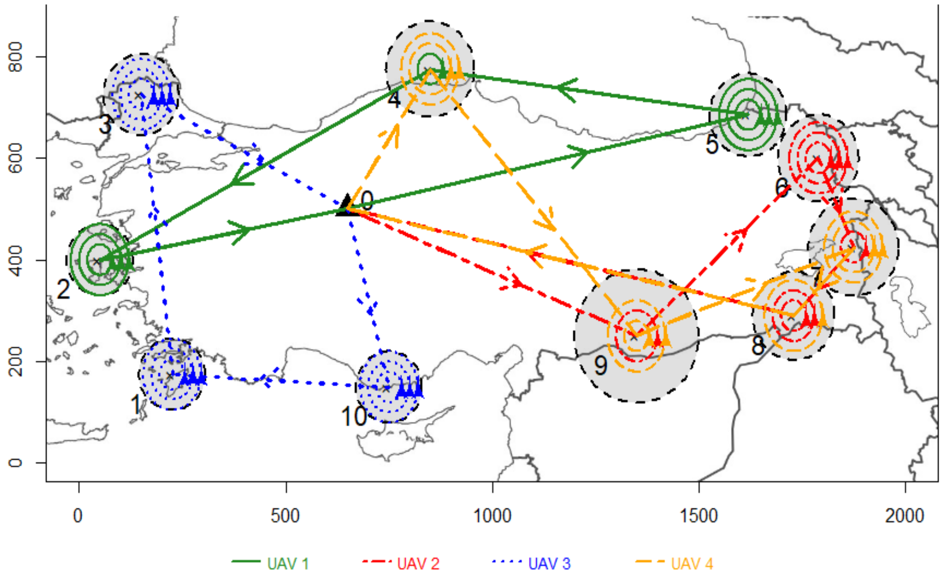

Figure 7. Demonstration of decisions in the operational level

4.5 Performance Evaluation of the Model on a Larger Instance

In practical UAV routing scenarios, the operational strategy typically does not encompass a large number of targets. This limitation arises from the distribution of adversaries within the mission terrain and the fuel capacity constraints of the UAVs. A considerable portion of the literature focuses on UAV movements between a single origin and destination, thereby restricting the number of nodes to two. Even among studies that consider multiple targets, the number of nodes involved is relatively modest. For instance, Dasdemir et al. (2020) investigate UAV routing problems with 5, 9, and 15 targets, while Moskal (2023) examines scenarios with 12, 16, and 28 targets. In this context, the problem instance, featuring 11 nodes (1 base and 10 targets), aligns well with practical scenarios and the scope of existing literature. It's worth noting that for border patrolling operations in Türkiye, scenarios involving more than the modeled 11 observation points are unlikely. However, the model possesses the flexibility to accommodate larger instances. To demonstrate this and investigate the computational performance of the model for larger instances, an instance with 21 nodes (1 base and 20 targets) nodes is generated. This size is large enough compared to literature, and it covers almost most of the part of Türkiye. The map of the instance is provided in Figure 8.

A computation is conducted to assess the model's performance across various combinations of constraints. In this evaluation, no low-level decision-making details are presented, as they hold greater relevance in the context of the actual case study. The primary focus here is on examining the computational performance of the model. The parameter settings employed were consistent with those outlined in the start of "Computations" section, with the exception that $T = 62$ and the termination condition is set to either a 3% gap or a 1-hour time limit. The other settings are $K = \{1, \ldots, k_{max}\}$, where $k_{max} \in \{8, 10, 12\}$, $F \in \{8, 16, 24\}$ and $\beta \in \{0.01, 0.03, 0.05\}$. This resulted in a total of 27 different combinations being tested.

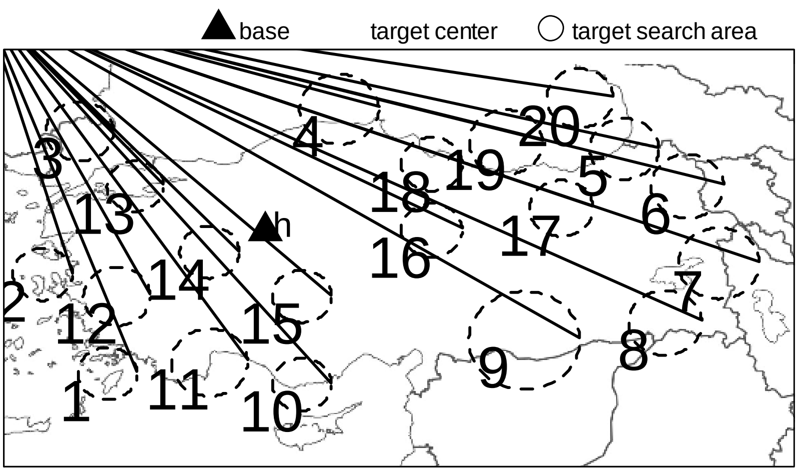

Figure 8. Larger problem instance with 1 base and 20 targets

The scatter plots in Figure 9 illustrate the variation in solution time against different mission durations, detection limits, and fleet sizes. The analysis reveals that cases terminating at the 3600-second mark are predominantly clustered at the lower end of the mission time spectrum. For lower probability scenarios (0.1), none reached an optimal solution within 3600 seconds, while the difference in distributions for 0.3 and 0.5 probabilities is not markedly significant. Additionally, the distribution of cases across different vehicle counts is relatively even, suggesting no clear correlation between the number of vehicles and the instances where solutions were not found within the set time frame.

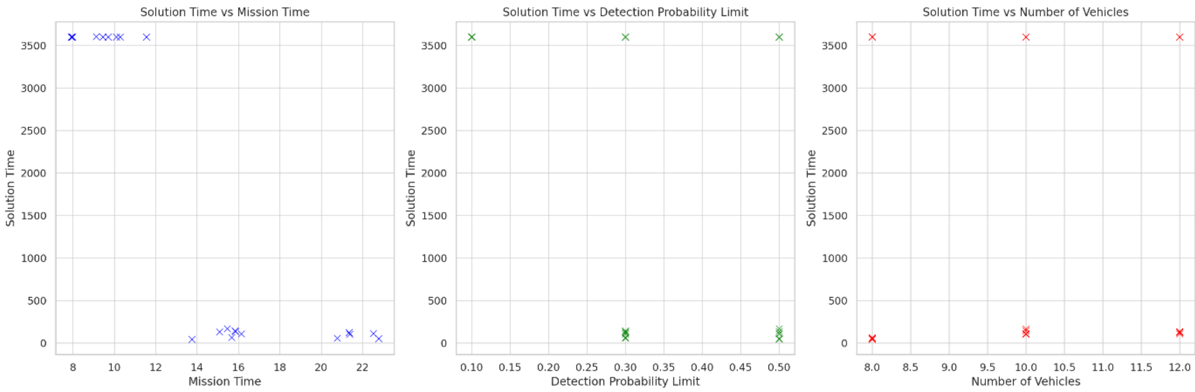

Figure 9. Scatter plots for the solution time of larger problem instance

Figure 10 presents the correlation between expected information collection and three mission parameters. For shorter missions, a broader range of expected information collection values is observed, while longer missions tend to show more clustering towards higher values. In terms of detection limitations, the results indicate that higher detection probability limits may not always result in substantially increased information collection, possibly due to other mission parameter limitations or operational constraints. Regarding fleet size, although larger fleets raise the minimum expected information collection, the relationship is not distinctly linear, suggesting that increasing fleet size does not uniformly enhance information collection.

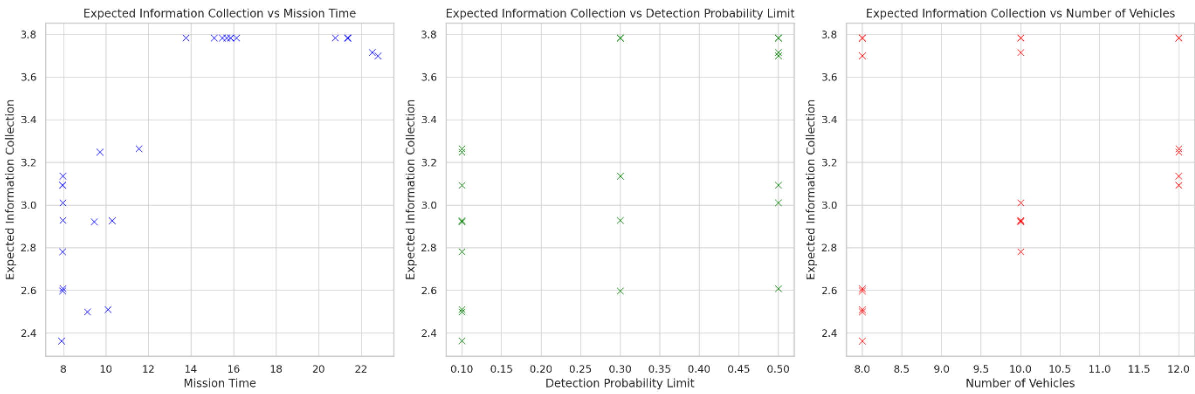

Figure 10. Scatter plots for the expected collected information of larger problem instance

4.6 Discussions

The case study, MO in the context of UAV operations for border patrolling in Türkiye, show the effectiveness of the model in addressing high and low-level decision problems during practical-sized UAV border patrolling operations. It provides optimal recommendations and reveals trade-offs among mission success (information collection), mission safety (radar threat), and mission duration (flight duration) in 18 minutes on average (with a median of 5) over 210 runs with different parameter combinations.

Innovation productivity, at its core, is about maximizing the output and value derived from innovative activities, and the effective conversion of new ideas into practical, value-adding applications. In the case, the application of MO in UAV operations highlights this motivation. By optimizing the UAV routes and strategies, MO not only improves the operational efficiency but also contributes to the broader objective of enhancing the productivity of the innovation. The ability to quickly analyze and determine optimal solutions in complex scenarios of innovative products, like UAV border patrolling, increases productivity in the innovation lifecycle. Decision makers can collect more relevant and higher-quality data in less time, which can then be analyzed to derive valuable insights. In applications like search and rescue or disaster management, optimized UAV missions can result in quicker response times. Over time, consistent optimization accumulates valuable operational experience and data, which can be used for ongoing research and development. This, in turn, leads to better UAV technology and more effective mission planning tools, fostering long-term innovation and increased productivity in the UAV industry. The proficiency of the model in optimizing a mission consideration can lead to benefits in others. For instance, optimizing for mission duration not only saves time but also potentially increases the frequency of missions, thereby amplifying the overall output of the UAV system. To sum up, optimizing UAV missions streamlines operations, cuts costs speeds up data collection, and ultimately results in more successful and productive outcomes.

5. CONCLUSION

The primary motivation behind a productive innovation is to achieve equal or greater output while utilizing the same or fewer resources, thereby generating added value. At each stage of the innovation process, design problems arise, and efficiently addressing these challenges can significantly boost innovation productivity.

In the current era of digital transformation, analytical approaches are being incorporated into the design problems in innovation management. One such candidate is MO, which is a rapidly growing field within AI that is often underestimated. Despite its long history, MO's impact has recently increased with the advancement of computing technology. What sets MO apart from popular fields like machine learning is its ability to provide optimal recommendations for design problems, guaranteeing their optimality. By leveraging MO methodologies in conjunction with powerful solver technologies, the limitations such as scalability, automation, and the complexity of learning that humans often face can be eliminated.

In this paper, utilization of MO for enhancing innovation productivity is explored. A framework is introduced for integrating MO into the design processes of innovation management. Additionally, a case study that exemplifies the practical application of MO in the utilization of a UAV fleet for border patrolling in Türkiye is presented. In the case study, particularly focusing on UAV operations for border patrolling in Türkiye, the substantial role of MO in boosting innovation productivity is demonstrated. MO’s application extends beyond UAV operations, offering broad potential in enhancing the productivity of diverse innovation processes. MO effectively optimizes product design and development, aligning features and specifications with customer needs while controlling costs, thereby expediting innovation cycles. It also enhances resource allocation efficiency, maximizing the return on investment and reducing wastage. In decision-making, MO delivers swift and optimal recommendations, shortening the transition from concept to execution and improving process efficiency. Furthermore, MO plays a crucial role in managing risks and uncertainties inherent in innovation, providing stability through scenario modeling. Additionally, MO facilitates continuous improvement, adapting to new data and insights for more effective solutions. Ultimately, MO's capacity to streamline various innovation aspects significantly reduces time to market, offering a competitive edge and reinforcing the productivity of the entire innovation cycle.

In Türkiye, innovation is as a key government policy, especially in the realm of technological advancement. The country focuses on developing products and services that can compete effectively on the global market. A prime example of this is Türkiye’s significant progress in the development and deployment of UAVs, with notable vehicles like Bayraktar TB2, Anka, TAI ANKA, and Vestel Karayel. These advancements places Türkiye at the forefront of this competitive field. Furthermore, Türkiye has initiated the production of EV equipped with autonomous driving capabilities and other intelligent solutions through TOGG. The scope of innovation extends beyond technology to include processes and services. Recently, the Turkish national space program was unveiled, underscoring the commitment to space exploration. In the world of e-commerce and food delivery platforms, Türkiye stands out as one of the most competitive nations. Furthermore, significant innovations have been achieved in the realm of digital healthcare services, evident in platforms like E-nabız and e-prescription. Therefore, integration of MO into innovation initiative’s in Türkiye provides a significant potential for innovation productivity.

The paper focuses on the potential of MO in enhancing innovation productivity, but there are still challenges that require further investigation and research. Many questions remain unanswered. One key question is the applicability of MO in triggering innovation. While MO is widely accepted in management areas, its use in pre-innovation stages is not yet well understood. Another question is about the availability of resources for a MO integration. Are MO-led design processes applicable in any industry or company, or are there limiting factors such as the availability of experts, suitable software, and the right organizational culture? Are these necessary resources available at reasonable costs, particularly in the context of Türkiye? Furthermore, integrating MO into design practice poses the challenge of determining the role of decision makers. With the availability of powerful computing, decision makers will no longer need to manually find solutions to problems. Instead, their role will shift towards understanding the significance of innovation problems, defining design problems, formulating them, and translating them into computer-based models. This shift may necessitate a reconsideration of innovation processes, organizational structures, and problem-solving approaches. While MO holds significant potential, these questions remain unanswered, and further exploration is needed to fully comprehend the implications and practical implementation of MO in innovation processes.

6. REFERENCES

Ackoff, R.L. (1979). "The Future of Operational Research is Past", *The Journal of the Operational Research Society,* 30(2)**,** 93-104.

Arf, C. (1959). "Makine Düşünebilir Mi ve Nasıl Düşünebilir?", *Atatürk Üniversitesi – Üniversite Çalışmalarını Muhite Yayma ve Halk Eğitimi Yayınları Konferanslar Serisi,* 1, 91-103.

Baykar (2023). "Bayraktar Akinci*"* https://baykartech.com/tr/uav/bayraktar-akinci/ (Access date: 29.03.2024).

Braekers, K., Ramaekers, K. and Van Nieuwenhuyse, I. (2016). "The Vehicle Routing Problem: State of the Art Classification and Review", *Computers & Industrial Engineering,* 99, 300-313.

Camm, J.D., Cochran, J.J., Fry, M.J. and Ohlmann, J.W. (2020). "Business Analytics", Cengage Learning*,* Boston*.*

Cantner, U., Dettmann, E., Giebler, A., Guenther, J. and Kristalova, M. (2019). "The Impact of Innovation and Innovation Subsidies on Economic Development in German Regions", *Regional Studies,* 53(9)**,** 1284-1295.

Carayannis, E. and Grigoroudis, E. (2014). "Linking Innovation, Productivity, and Competitiveness: Implications for Policy and Practice", *The Journal of Technology Transfer,* 39(2)**,** 199-218.

CCR (University at Buffalo), (2024). “The Center for Computational Research”, http://hdl.handle.net/10477/79221, (Erişim tarihi: 29.03.2024)

Cockburn, I.M., Henderson, R. and Stern, S. (2019). "The Impact of Artificial Intelligence on Innovation: An Exploratory Analysis ", *In:* Agrawal, A., Gans, J. and Goldfarb, A. (eds.) *The economics of artificial intelligence : an agenda.* Chicago ; London : The University of Chicago Press.

Coutinho, W.P., Battarra, M. and Fliege, J. (2018). "The Unmanned Aerial Vehicle Routing and Trajectory Optimisation Problem, A Taxonomic Review", *Computers & Industrial Engineering,* 120, 116-128.

Dasdemir, E., Batta, R., Köksalan, M. and Tezcaner Öztürk, D. (2022). "UAV Routing for Reconnaissance Mission: A Multi-Objective Orienteering Problem with Time-dependent Prizes and Multiple Connections", *Computers & Operations Research,* 145, 105882.

Dasdemir, E., Köksalan, M. and Tezcaner Öztürk, D. (2020). "A Flexible Reference Point-Based Multi-Objective Evolutionary Algorithm: An Application to the UAV Route Planning Problem", *Computers & Operations Research,* 114, 104811.

Elmokadem, T. and Savkin, A.V. (2021). “Towards Fully Autonomous UAVs: A Survey”. *Sensors*, 21.

Evers, L., Barros, A. I., Monsuur, H. and Wagelmans, A. (2015). "UAV Mission Planning: From Robust to Agile", *Military Logistics: Research Advances and Future Trends, (*Editors: Zeimpekis, V., Kaimakamis, G. and Daras, N.J), . Springer International Publishing, Cham.

Garud, R., Tuertscher, P. and Van de Ven, A.H. (2013). "Perspectives on Innovation Processes", *Academy of Management Annals,* 7(1)**,** 775-819.

Guerriero, F., Surace, R., Loscri, V. and Natalizio, E. (2014). "A Multi-Objective Approach for Unmanned Aerial Vehicle Routing Problem with Soft Time-Windows Constraints", *Applied Mathematical Modelling,* 38(3)**,** 839-852.

Gunawan, A., Lau, H.C. and Vansteenwegen, P. (2016). "Orienteering Problem: A Survey of Recent Variants, Solution Approaches and Applications", *European Journal of Operational Research,* 255(2)**,** 315-332.

Gurobi Optimization, LLC. 2024. Gurobi Optimizer Reference Manual.

Haefner, N., Wincent, J., Parida, V. and Gassmann, O. (2021). "Artificial Intelligence and Innovation Management: A Review, Framework, and Research Agenda", *Technological Forecasting and Social Change,* 162, 120392.

Haenlein, M. and Kaplan, A. (2019). "A Brief History of Artificial Intelligence: On the Past, Present, and Future of Artificial Intelligence", *California Management Review,* 61(4)**,** 5-14.

Hall, J.R. and Hess, S.W. (1978). "OR/MS: Dead or Dying? RX for Survival", *Interfaces,* 8, 42-44.

Jacques, B., Eric, H., Sree, R., Chui, M. , Allas, T., Dahlstrom, P., Henke, N. and Trench, M. (2017). "Artificial Intelligence: The Next Digital Frontier?", McKinsey and Company Global Institute, 47.3.6,

Mariani, M.M., Machado, Isa, M.V. and Dwivedi, Y.K. (2023). "Artificial Intelligence in Innovation Research: A Systematic Review, Conceptual Framework, and Future Research Directions", *Technovation,* 122, 102623.

McCloskey, J.F. (1987). "The Beginnings of Operations Research: 1934-1941", *Operations Research,* 35(1)**,** 143-152.

Minford, L. and Meenagh, D. (2019). "Testing a Model of UK Growth: A Role for R&D Subsidies", *Economic Modelling,* 82, 152-167.

Mittal, S. and Deb, K. (2007), “Three-Dimensional Offline Path Planning for UAVs Using Multiobjective Evolutionary Algorithms”, *2007 IEEE Congress on Evolutionary Computation*, Singappre, 3195-3202.

Mittelmann, H.D. (2020). "Benchmarking Optimization Software - A (Hi)Story", *SN Operations Research Forum,* 1(1)**,** 2.

Moskal, M.D. and Batta, R. (2017). "A Macrogrid Approach for Routing UAVs in Support of Information Gathering", *Military Operations Research,* 22(4)**,** 35-54.

Moskal, M.D., Dasdemir, E.and Batta, R. (2023). "Unmanned Aerial Vehicle Information Collection Missions with Uncertain Characteristics", *INFORMS Journal on Computing,* 35(1)**,** 120-137.

Moustakas, K., Loizidou, M., Rehan, M. and Nizami, A. S. (2020). "A Review of Recent Developments in Renewable and Sustainable Energy Systems: Key Challenges and Future Perspective", *Renewable & Sustainable Energy Reviews,* 119

Pfeiffer, B., Batta, R., Klamroth, K. and Nagi, R. (2009). "Path Planning for UAVs in the Presence of Threat Zones Using Probabilistic Modelling", *Handbook of Military Industrial Engineering,* (Editors: Badiru, A. B. and Thomas, M. U.), CRC Press, USA.

Picchi, A. (2023). “College Majors Have A Big Impact on Income. Here Are the Highest- and Lowest-Earning Fields”, https://www.cbsnews.com/news/college-major-top-and-lowest-earning-majors-impact-on-income-pay/, (Access Date: 29.03.2024)

Rojas V., Daniela, Solano-Charris, E.L., Muñoz-Villamizar, A. and Montoya-Torres, J.R. (2021). "Unmanned Aerial Vehicles/Drones in Vehicle Routing Problems: A Literature Review", *International Transactions in Operational Research,* 28(4)**,** 1626-1657.

Rothberg, E. (Forbes), (2021). “Operations Research Analyst: The Fastest-Growing Job You've Never Heard of”. *https://www.forbes.com*(Access Date: 29.03.2024)

Sabuncuoğlu, İ. and Dengiz, B. (2022). "Türkiye’de Endüstri Mühendisliğine Bir Bakış: Geçmişi, Bugünü Ve Geleceği", *Verimlilik Dergisi,* 3**,** 559-568.

Stavropoulou, F., Repoussis, P.P. and Tarantilis, C.D. (2019). "The Vehicle Routing Problem with Profits and consistency constraints", *European Journal of Operational Research,* 274(1)**,** 340-356.

Teece, D.J. (2018). "Tesla and the Reshaping of the Auto Industry", *Management and Organization Review,* 14(3)**,** 501-512.

Tezcaner, D. and Köksalan, M. (2011). "An Interactive Algorithm for Multi-objective Route Planning", *Journal of Optimization Theory and Applications,* 150(2)**,** 379-394.

Tezcaner Öztürk, D. and Köksalan, M. (2023). "Biobjective Route Planning of An Unmanned Air Vehicle in Continuous Space", *Transportation Research Part B: Methodological,* 168, 151-169.

Verganti, R., Vendraminelli, L. and Iansiti, M. (2020). "Innovation and Design in the Age of Artificial Intelligence", *Journal of Product Innovation Management,* 37(3)**,** 212-227.

Xia, Y., Batta, R. and Nagi, R. (2017). "Controlling a Fleet of Unmanned Aerial Vehicles to Collect Uncertain Information in a Threat Environment", *Operations Research,* 65(3)**,** 674-692.

Zheng, Z. B., Xie, S.A., Dai, H.N., Chen, X.P. and Wang, H.M. (2018). "Blockchain Challenges and Opportunities: A Survey", *International Journal of Web and Grid Services,* 14(4)**,** 352-375.